Pennsylvania Climate Change Impacts Assessment Update

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Executive Summary

Introduction

The Pennsylvania Climate Change Act (PCCA), Act 70 of 2008, directed Pennsylvania's Department of Environmental Protection (DEP) to conduct a study of the potential impacts of global climate change on Pennsylvania over the next century and to prepare periodic updates. The first study was issued by DEP in 2009. It was prepared by a team of researchers at the Pennsylvania State University and presented to DEP in two reports: ***Pennsylvania Climate Impacts Assessment*** (Shortle et al., 2009), and ***Economic Impacts of Projected Climate Change in Pennsylvania*** (Abler et al. 2009). Updates were issued 2013 and 2015. This report is the third update. Like the first report and subsequent updates, this report has been prepared by a team of topic experts from Penn State University.

Prior reports have summarized research on Pennsylvania's climate future with global climate change. These reports have also assessed the impacts of climate change on climate-sensitive sectors in Pennsylvania, including agriculture, energy, forests, human health, outdoor recreation, water and aquatic resources. This has been a standard format for national and regional assessments. However, current expectations about Pennsylvania's projected future climate remain as presented in the 2015 report. Similarly, general expectations about climate change impacts on Pennsylvania's climate sensitive sectors remain largely as presented in the 2015 report.

Given the substantial understanding that Pennsylvania has been experiencing climate change and will continue to do so for the foreseeable future, there is a need for explicit understanding of risks and adaptation options to support decision making to cope with climate change. Accordingly, this report builds on and expands our prior work to provide a deeper orientation towards coping with climate change in high risk sectors. The goal in this report is to initiate a more comprehensive look than in the prior reports at specific climate risks and how public and private decision makers in the Commonwealth can prepare for them in high priority areas. In doing so, we take advantage of recent advances in research on climate change impacts in these areas.

This report focuses on three topic areas: (1) Climate change impacts on Pennsylvania livestock production and livestock production impacts on water quality; (2) Implications of climate change for planning, policies, and practices to achieve Pennsylvania's obligations under the 2011 Chesapeake Bay TMDL; and (3) Resilience of Pennsylvania's critical infrastructure to extreme weather and climate. These topics are addressed in order in Chapters 2,3, and 4 of this report.

An important theme in climate risk management science is the importance of refined characterizations of climate-related hazards to the design of efficient and effective climate risk management strategies. Rainfall and runoff events are the primary weather drivers of nonpoint pollution processes in agriculture and urban stormwater, and in the flood events highlighted in Chapters 3 and 4. Understanding what is known about extreme precipitation risks and research needs to improve understanding is of critical importance for addressing pollution and flood risks. Also important is understanding and facilitating the utilization of such information for climate risk management. These questions are addressed in Chapter 5. The emphasis in this chapter is on flood risks.

The format of the report, the selection of sectors, and the specific issues addressed within each of these three areas for this report were determined through a set of discussions between the Department of Environmental Protection and the Penn State research team on how to maximize the value of the update to the Commonwealth.

Climate Impacts on Livestock

Livestock production has an intrinsic relationship with climate. Dairy, beef, and livestock feed production in Pennsylvania occurs mostly or entirely in the open air, exposed to the elements and dependent on the weather for success. Most poultry and hog production in Pennsylvania takes place indoors, but even there climate directly impacts heating and cooling costs.

This work on livestock production in this project has two objectives. The first is to make projections for 2050 of the potential impacts of climate change on the size of the livestock industry in Pennsylvania (dairy, beef, pork, and poultry). This work considers both the direct impacts of climate change within Pennsylvania itself and indirect impacts of climate change on livestock industry location decisions between Pennsylvania and other parts of the U.S. and world. Second, using results from the first objective, this report makes projections for 2050 of potential impacts of climate change on nutrients from livestock production.

Climate change and increasing atmospheric CO_2 concentrations may have several large direct impacts on livestock yields and production costs in Pennsylvania. These include changes in forage productivity, protein content, and digestibility; changes in on-farm feed grain yields and quality; changes in prices of purchased feeds; heat stress and its impacts on livestock productivity and fertility; maintenance costs for livestock during periods of cold weather; for livestock housed indoors, changes in heating, cooling, and ventilation costs; and changes in livestock parasites, pathogens, and disease vectors.

Climate change may also have potentially large indirect impacts on Pennsylvania through livestock industry location decisions. Apart from watery dairy products like fluid milk and ice cream, where distribution costs limit the distance that products can be economically shipped, markets for most livestock products are national or international in scope. Currently, a large portion of U.S. hog and poultry production is concentrated in warmer, more southern states. Since climate control is a substantial input into the growth of these livestock, climate change could stimulate movement of poultry and hog production northward into states like Pennsylvania.

Large-scale livestock production serves as a nutrient concentrator on the landscape because a large proportion of the nutrients in feed are typically spread on land on or near livestock farms in the form of manure, often creating high nitrogen and phosphorus concentrations in the topsoil that act as a pollution source.

We use a “climate analogue” methodology to examine how climate change could impact livestock inventories in Pennsylvania. There are no data for Pennsylvania on how livestock producers would adjust their inventories in response to a future climate because Pennsylvania’s future climate is projected to be quite different from any climate in Pennsylvania’s history. Instead, we analyze livestock inventories in other parts in the U.S. that currently have a climate similar to Pennsylvania’s projected future climate. We do this statistically, using county-level data for the 48 contiguous states, while statistically controlling for other (non-climate) factors impacting livestock inventories in each county. We examine inventories of dairy cows, beef cattle, hogs and pigs, and poultry. We combine our statistical results on the impacts of climate on livestock inventories with county-level projections of Pennsylvania’s future climate for the mid-21st century in order to project changes in livestock inventories due to climate change.

Our projections suggest that climate change could lead to significant changes in the product composition and spatial distribution of Pennsylvania’s livestock industry between 2012 and 2050. Climate change could cause Pennsylvania’s poultry inventory to more than double in size. Much smaller, but still positive, increases in inventory could occur for beef cattle and hogs and pigs. The projected impact of climate change of dairy inventory for Pennsylvania as a whole is about zero, but there could be a spatial rearranging of the dairy industry within Pennsylvania. Milk cow inventories in southeast counties that are currently the heart of Pennsylvania’s dairy industry are projected to decline, while inventories in northwest counties are projected to rise. For beef cattle, inventories are projected to increase modestly throughout Pennsylvania, with the largest percentage increases in the northwest counties. On the other hand, the largest projected percentage increases in hog/pig inventories are in the southeastern counties, while the smallest increases or declines are in the northern and northwest counties.

Projected changes in nitrogen and phosphorus in animal manure between 2012 and 2050 due to climate change show increases throughout almost all of Pennsylvania. These changes could exacerbate current water quality concerns with excess nutrients in livestock manure, especially in the Susquehanna and Delaware River Basins.

Climate Change Impacts on Pennsylvania’s Watershed Management Strategies and Water Quality Goals

Pennsylvania is required by the Chesapeake Bay Total Maximum Daily Load (TMDL) to meet specific nutrient pollution load reductions requirements by 2025. The practices and methods that the state seeks to have implemented to achieve these requirements are set forth in “Final Phase 3 Watershed Implementation Plan” (Phase 3 WIP). Underlying the Phase 3 WIP is an understanding of the relationships between land uses and pollution control practices embodied in the US EPA Chesapeake Bay Watershed Model (CBWM).

Assessments of the effectiveness of the Phase 3 WIP have been made using the CBWM based on climate data from the 20th century. Expected climate change will, however, impact drivers of water quality throughout the Bay watershed. CBWM simulations that examine the impacts of climate change across the Bay watershed indicate that nutrient loads will increase without appropriate adaptations. Accordingly, local and countywide planning associated with the Phase 3 WIP should also consider these changing conditions. Changes to temperature and precipitation patterns will impact nonpoint pollution and the management strategies used to reduce the delivery of sediment and nutrients from agricultural and urban landscapes to waterways across the Commonwealth. These changes may impact the magnitude and frequency of large precipitation events, resulting in decreased effectiveness of BMPs.

Recent case studies in Pennsylvania focusing on climate change impacts on wetland hydrology, forested riparian buffers in agricultural watersheds, and landscape analysis across the state indicate heterogeneity in both landscapes and their response to uniform climate drivers. These case studies highlight the need for updated management strategies that incorporate spatially targeted, smart, and resilient BMPs.

Adjustments to BMP design and location will be needed to mitigate increased and more frequent runoff events, and the spatial variation of climate change impacts within watersheds and across the state will require strategic distribution of resources to prioritize critical locations and watersheds. Climate change may also impact the efficiency of some BMPs, necessitating BMP evaluation criteria focusing on this potential reduction in performance as well as overall resilience to specific climate change impacts. Structural BMPs may be more vulnerable to the impacts of climate change than non-structural BMPs, as adaption strategies will need to be incorporated into design standards and criteria identifying long-term placement and maintenance. Management plans building resiliency into BMPs will require cost-effective, spatially strategic smart strategies to maximize the impact of resources and provide flexibility to heterogenous landscapes and site-specific challenges. Finally, use of the best available data and modeling results should be part of all new BMP design and maintenance plans to ensure limited resources are utilized in the most efficient and impactful way.

Climate Change and Pennsylvania's Infrastructure

As the climate in Pennsylvania is projected to change over the course of the present century, the ways in which weather and other events related to the climate affect major infrastructures is also likely to change. Some types of impacts on infrastructure, particularly those related to flooding and extreme heat, are likely to increase. Other types of impacts, particularly those related to extreme cold, may decrease as Pennsylvania becomes warmer. The entities that plan and operate infrastructure in Pennsylvania, whether they are public entities or private industry, are likely to need to adapt physical infrastructure to a changing climate.

Pennsylvania's infrastructure systems – its energy, transportation and water networks – are both regionally and nationally important and are also highly interdependent. Single events such as floods or other extreme weather events may have direct impacts on some infrastructure systems, and these direct impacts may cascade through to multiple interdependent systems (illustrated in Figure ES-1). Assessments of Pennsylvania's climate futures generally indicate that the Commonwealth is likely to become more susceptible to some kinds of extreme weather conditions, such as flooding and extended periods of heat, that may stress multiple infrastructures simultaneously.

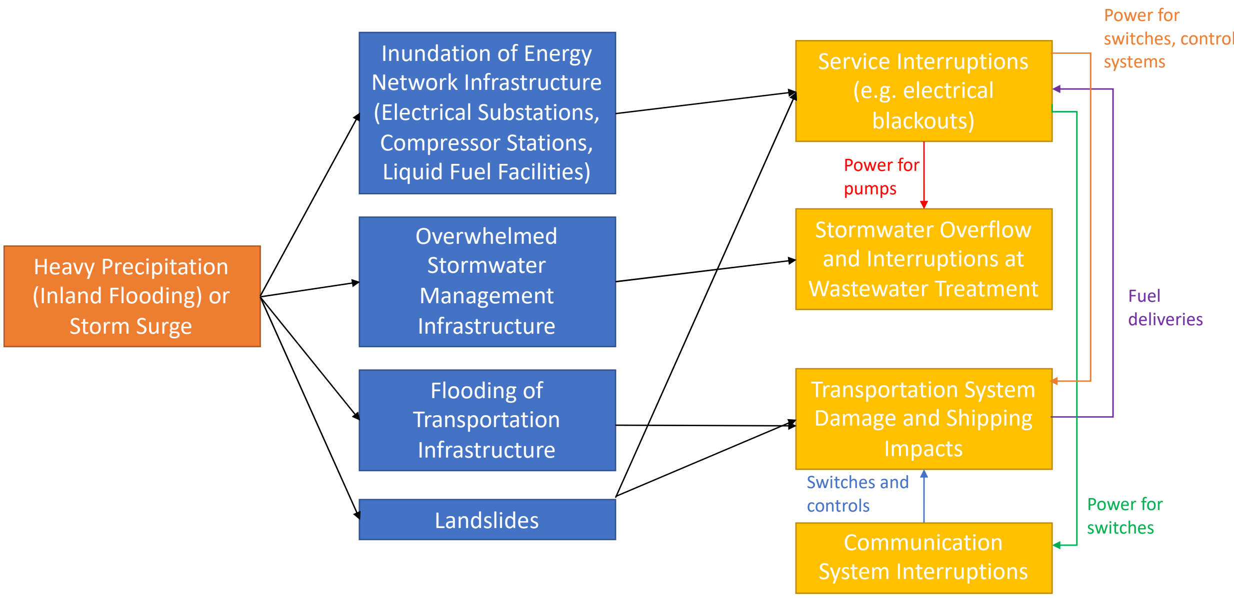

Figure ES-1: Illustrating Infrastructure Interdependencies. An initiating event (heavy precipitation or storm surge in this case) may directly affect multiple infrastructure systems as shown in the blue boxes. The impacts may cascade between systems, as shown in the yellow boxes and colored arrows.

The infrastructure section of the 2018 Update to Pennsylvania Climate Impacts synthesizes existing studies and information on how these climactic changes may affect the functioning of infrastructure systems in Pennsylvania, and to characterize possible changes in frequency and intensity of extreme weather events as Pennsylvania's climate changes. We have several key findings:

- Flooding (related either to extreme precipitation or coastal storm surge in Southeastern Pennsylvania in particular) appears to have the most potential future impact on infrastructure systems in Pennsylvania.
- Drought and extreme heat may also pose challenges for infrastructure in Pennsylvania. Extreme heat in particular has been associated with public health challenges, and represents an adaptation need for Pennsylvania's infrastructure.
- Flood-related damage to infrastructure is likely to be very localized in nature. For example, flooding may cause local blackouts but by itself is unlikely to bring down the regional power grid. Localized flooding could, in some circumstances, disrupt rail and other transportation networks in ways that could have impacts on other infrastructure systems or broader economic activity.
- Large portions of multiple energy and transport infrastructures in Pennsylvania are potentially susceptible to direct damage from flooding. Particularly in the Southwestern portion of Pennsylvania, infrastructures face additional risk exposure from landslide potential associated with heavy precipitation events.
- Infrastructure planning to adapt to a changing climate occurs along multiple scales, with some decisions made locally and others made regionally or even nationally. Some of these planning processes have incorporated possible climate impacts while others have not.

- The impacts of extreme weather effects on infrastructure varies widely across Pennsylvania, with different counties having very different annual damages as well as a per-capita damage burden. Infrastructure readiness to cope with flooding and extreme heat events varies widely across Pennsylvania – some counties that appear to be the hardest hit historically are also among the poorest in the state.

Past and Potential Future Precipitation Changes in Pennsylvania

Climate model projections suggest that extreme precipitation will become more intense and frequent in the 21st century, with potentially large impacts. The design of climate risk management strategies can be improved by a refined characterization of climate-related hazards. Understanding extreme precipitation is a high priority for climate risk management related to flooding, water pollution, and other climate risks in Pennsylvania. Pertinent research on observed and projected precipitation extremes is examined and summarized with a focus on changes in average and extreme precipitation. Recent research on local-level decisions that depend on precipitation simulations is also examined.

There is a sizeable body of research that can already provide useful climate information. Yet, there is a considerable gap between the resolution required for agricultural and urban land use and infrastructure management and climate model resolutions. Current flood hazard and projections are deeply uncertain. This does not imply that decisions (for example about the design of infrastructure) cannot be improved by considering these deeply uncertain projections. Rather, the decision-analytical procedures have to account for the deep and dynamic uncertainties (for example by using the approach of many-objective robust decision making).

There are still many open research questions. Examples for these questions include:

1. What is the main driver of flooding in Pennsylvania?
2. What are the uncertainties surrounding the precipitation projections?
3. Which uncertainties related to precipitation projections (e.g., time-scale, percentile) are most decision-relevant?
4. What potential changes in observing systems, data analysis methods, and modeling techniques have the greatest potential for reducing these decision-relevant uncertainties?

Chapter 1 Climate Change and Livestock Production in Pennsylvania*

David Abler, Asif Rasool, Xuetao Huang, and James Shortle

1. Introduction

Livestock production has an intrinsic relationship with climate. Dairy, beef, and livestock feed production in Pennsylvania occurs mostly or entirely in the open air, exposed to the elements and dependent on the weather for success. Most poultry and hog production in Pennsylvania takes place indoors, but even there climate directly impacts heating and cooling costs.

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Climate change may also have potentially large indirect impacts on Pennsylvania through livestock industry location decisions. Apart from watery dairy products like fluid milk and ice cream, where distribution costs limit the distance that products can be economically shipped, markets for most livestock products are national or international in scope. Currently, a large portion of U.S. hog and poultry production is concentrated in warmer, more southern states. Since climate control is a substantial input into the growth of these livestock, climate change could stimulate movement of poultry and hog production northward into states like Pennsylvania (Shortle et al., 2015).

Large-scale livestock production serves as a nutrient concentrator on the landscape because a large proportion of the nutrients in feed are typically spread on land on or near livestock farms in the form of manure, often creating high nitrogen and phosphorus concentrations in the topsoil that act as a pollution source. The direct effects of climate change on livestock and, in turn, water quality are mixed: greater precipitation and storm intensity may increase leaching loss of

* This report is a deliverable for a Penn State contract with the Pennsylvania Department of Environmental Protection (DEP), PA 2018 Climate Change Impact Assessment, purchase order #4300615517 and contract #4400015622. The authors would like to thank Dr. Robert Nicholas at Penn State for facilitating access to the climate data used in this report. The authors would also like to thank DEP staff for their consultations during the work on this report.

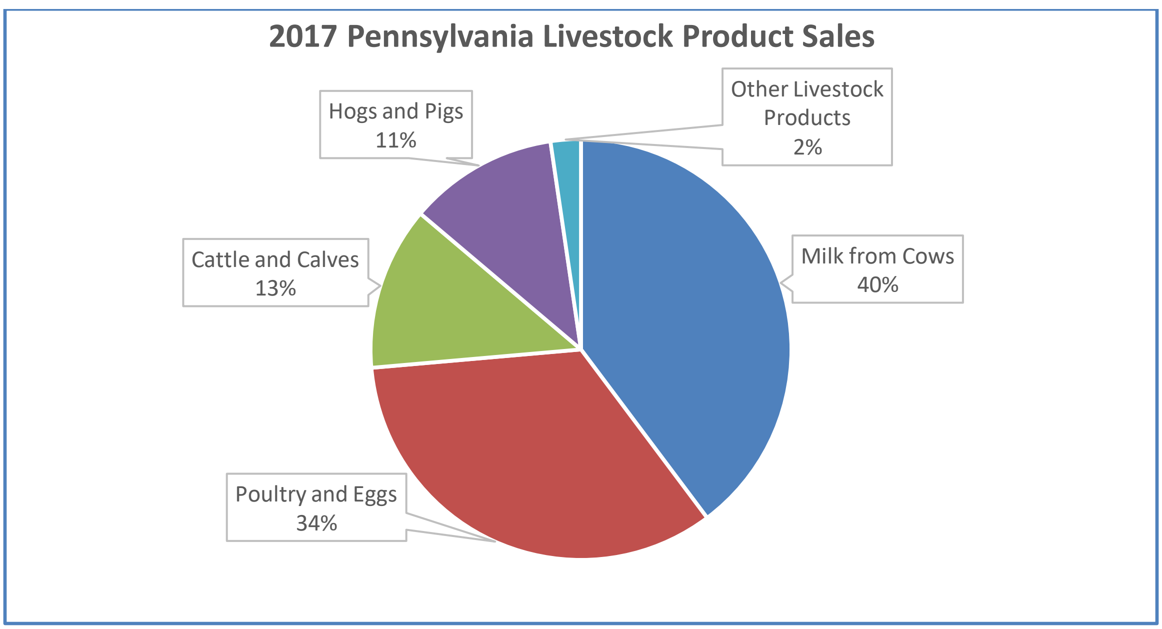
nitrogen and phosphorus, but a longer growing season and higher temperatures may increase plant uptake of nutrients, reducing leaching potential (Hristov et al., 2018; Rojas-Downing et al., 2017). Indirect effects arising through livestock industry location decisions depend on how much relocation to Pennsylvania occurs, and on nutrient management practices by new livestock producers in Pennsylvania.

This report finds that climate change between 2012 and 2050 could lead to the following:

- Pennsylvania's poultry inventory could more than double in size. Much smaller, but still positive, increases in inventory could occur for beef cattle and for hogs and pigs, but not for dairy.
- There could be a spatial rearranging of the dairy industry within Pennsylvania. Milk cow inventories in southeast counties that are currently the heart of Pennsylvania's dairy industry could decline, while inventories in northwest counties could rise.
- Quantities of nitrogen and phosphorus in animal manure could increase in almost all of Pennsylvania's counties, and significantly so in south-central and southeast Pennsylvania if poultry manure is included in the calculations.

2. Present-Day Pennsylvania Livestock Industry

According to the 2017 Census of Agriculture (USDA, National Agricultural Statistics Service 2019), there are approximately 53,000 farms in Pennsylvania, more than half of whom (52%) sell livestock products. Total sales of livestock products in 2017 were about $5 billion, representing nearly two-thirds (64%) of all agricultural product sales. Milk from cows accounted for 40% of total livestock product sales, followed by poultry and eggs (34%), cattle and calves (13%), hogs and pigs (11%), and all other livestock products (2%).

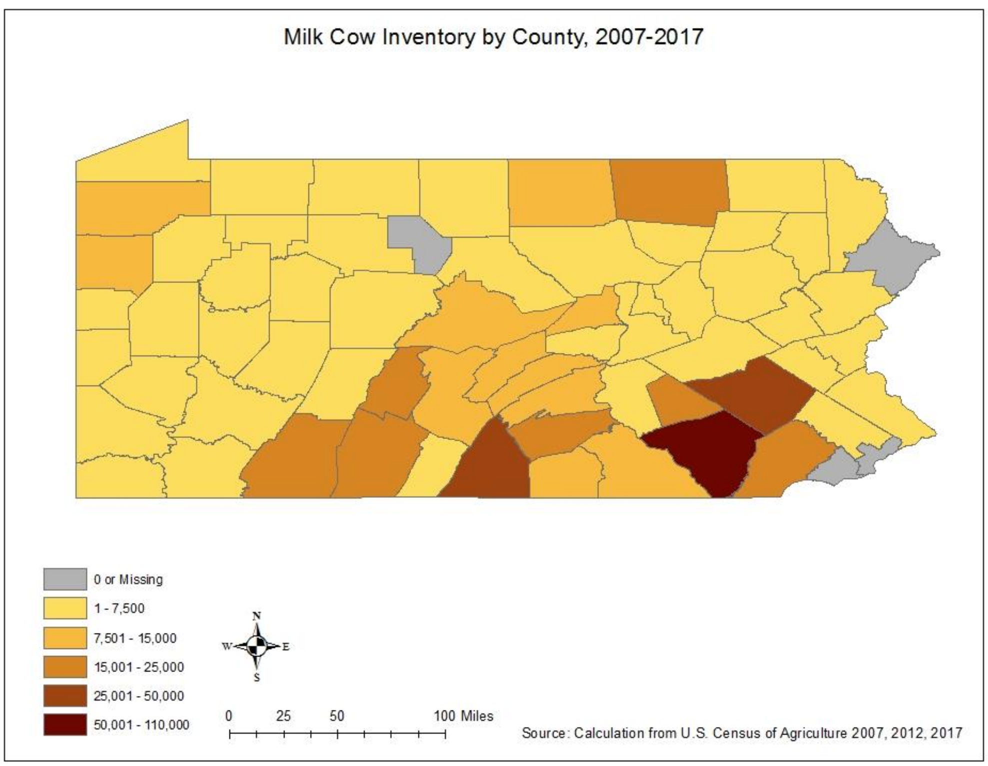


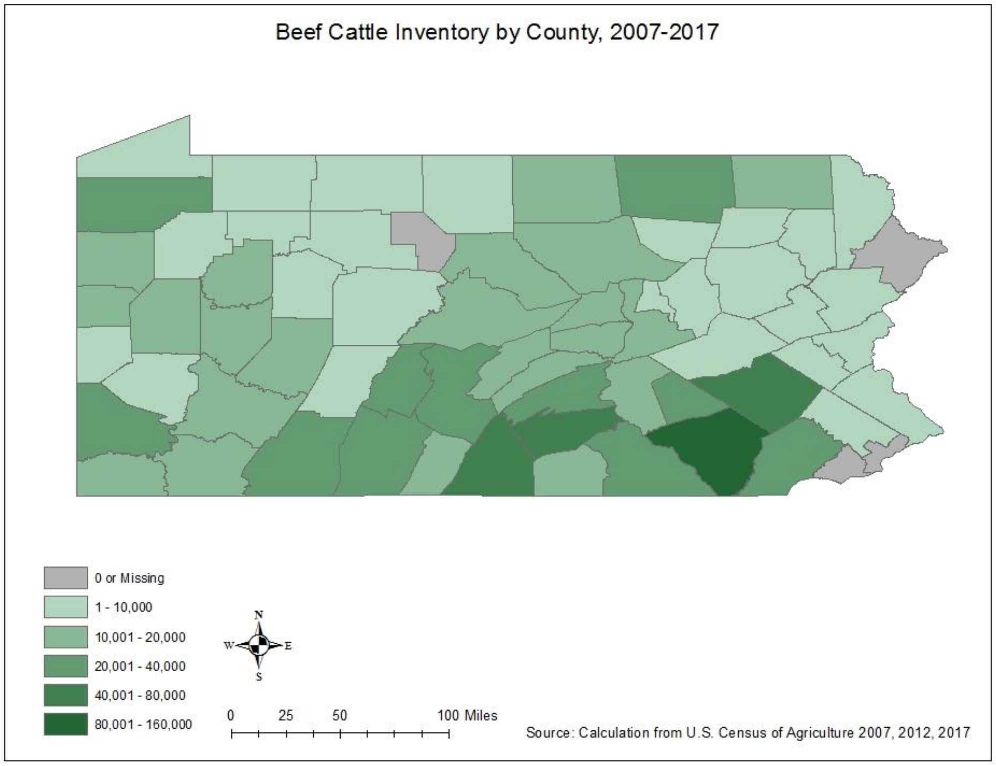
Pennsylvania farms in 2017 had a total of about 7.3 million acres of land, of which nearly one million acres (14%) were pastureland—either permanent pastures, pastured cropland, or pastured woodland. Harvested cropland, most of which produces feed for livestock, accounted for 54% of total farmland.

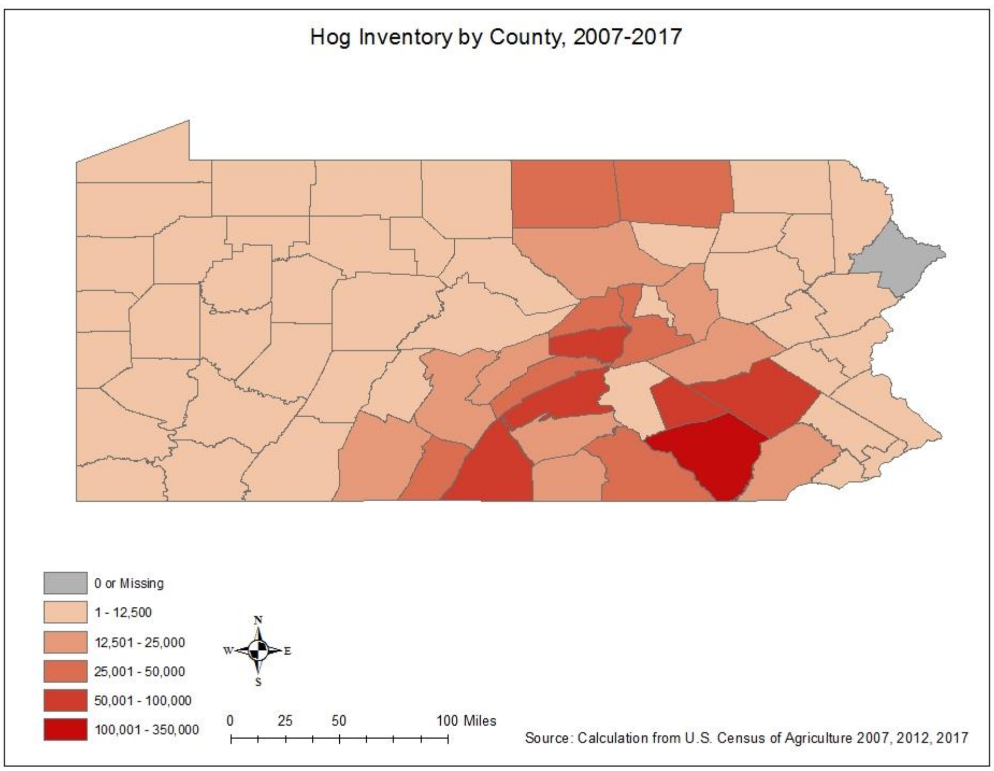
Most dairy and beef farms in Pennsylvania are small compared to other regions of the United States. For Pennsylvania, the average milk cow herd size per farm in 2017 was 144, and 43% of dairy farms had fewer than 50 milk cows. The average beef cow herd size per farm in 2017 was 39, and 71% of beef farms had fewer than 20 beef cows.

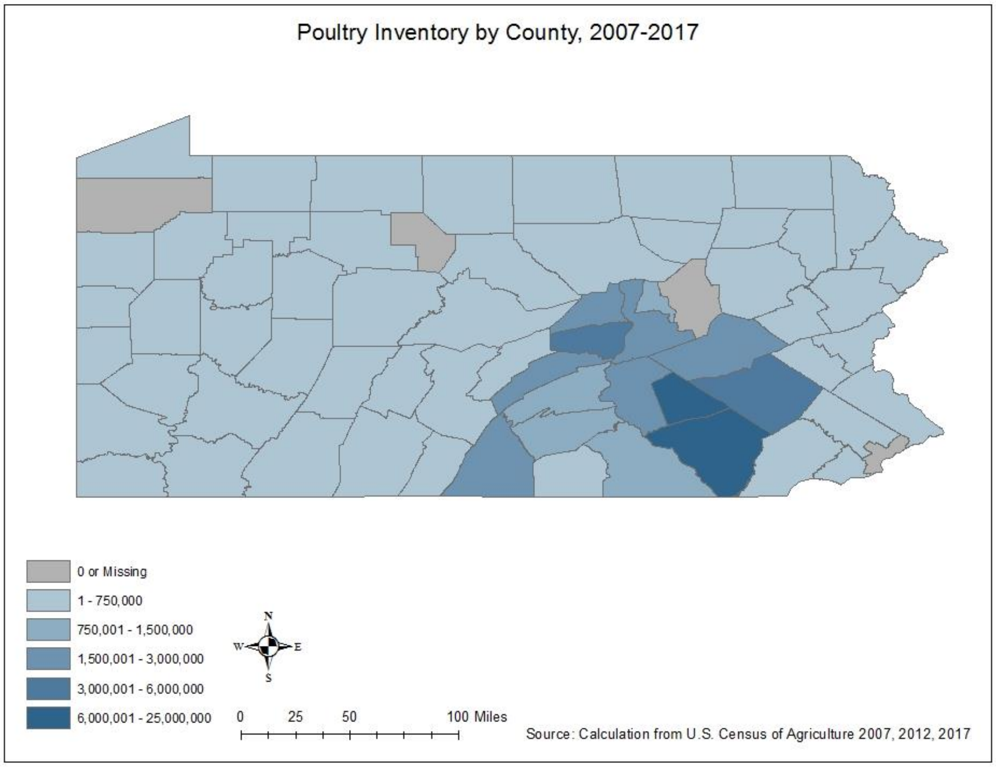
Pork and poultry farms in Pennsylvania are more like the rest of the country in that there are many small farms, but production is concentrated in a small number of large farms. For hogs and pigs, nearly three-fourths (73%) of farms had a herd size of less than 25. However, the largest 2% of farms (herd size of 5,000 or more) had 43% of total Pennsylvania hog and pig inventory, and the largest 8% of farms (herd size of 2,000 or more) had 84% of total inventory. For chicken layers, the largest 3% of farms (flock size of 50,000 or more layers) had 59% of total inventory, and for chicken broilers, the largest 17% of farms (flock size of 300,000 or more broilers) had 79% of total inventory.

The maps and table below show the distribution across counties in Pennsylvania of inventories of milk cows, beef cattle, hogs and pigs, and poultry. The figures for each county are averages across the Census of Agriculture years 2007, 2012, and 2017. Taking an average across years smooths out year-to-year fluctuations in inventories due to ups and downs in livestock product prices, feed costs, energy costs, and other factors. Milk cow and hog/pig inventories are available directly from the Census of Agriculture. The inventory of beef cattle is defined as inventory of all cattle and calves minus inventory of milk cows. Poultry inventory is defined as the sum of inventories of chicken broilers, chicken layers, and chicken pullets.




Beef Cattle Inventory by County, 2007-2017
0 or Missing
1 - 10,000
10,001 - 20,000
20,001 - 40,000
40,001 - 80,000
80,001 - 160,000
N
W
E
S
0
25
50
100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017


Hog Inventory by County, 2007-2017
0 or Missing
1 - 12,500
12,501 - 25,000
25,001 - 50,000
50,001 - 100,000
100,001 - 350,000
N
W
E
S
0
25
50
100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017



Livestock Inventories by County, 2007–2017

County	Milk Cows	Beef Cattle	Hogs & Pigs	Poultry
Adams	7,920	18,783	12,758	691,569
Allegheny	74	2,151	154	8,667
Armstrong	3,206	11,502	850	4,755
Beaver	1,675	5,671	1,262	3,381
Bedford	15,586	30,466	18,100	150,308
Berks	26,010	51,279	72,013	4,876,751
Blair	18,547	21,582	2,822	21,555
Bradford	17,210	37,863	49,967	7,310
Bucks	2,129	5,575	563	14,361
Butler	2,826	13,313	1,051	6,533
Cambria	2,062	6,929	583	3,118
Cameron	—	—	99	—
Carbon	105	1,233	110	1,489
Centre	10,838	18,278	3,848	55,242
Chester	19,796	22,751	22,444	680,946
Clarion	2,445	11,065	1,188	2,970
Clearfield	1,181	4,234	279	2,159
Clinton	5,316	13,780	4,722	156,959
Columbia	3,041	6,670	13,333	—
Crawford	12,290	24,289	1,575	—

County	Milk Cows	Beef Cattle	Hogs & Pigs	Poultry
Cumberland	18,914	44,108	21,684	1,242,556
Dauphin	5,466	10,270	11,239	2,039,483
Delaware	—	—	18	381
Elk	440	1,931	161	4,976
Erie	4,700	9,464	818	17,534
Fayette	2,614	12,716	1,748	5,040
Forest	192	430	43	459
Franklin	47,416	79,775	73,860	2,634,589
Fulton	5,542	12,930	32,512	2,160
Greene	569	11,613	133	2,035
Huntingdon	12,225	20,808	15,487	378,848
Indiana	6,404	16,860	1,592	6,483
Jefferson	1,949	7,707	652	2,907
Juniata	8,065	12,626	28,506	2,456,754
Lackawanna	1,079	2,380	90	17,588
Lancaster	108,962	157,188	342,770	24,336,565
Lawrence	4,321	10,435	1,488	6,545
Lebanon	24,755	35,439	97,435	6,340,315
Lehigh	1,287	2,543	3,123	11,426
Luzerne	723	2,734	358	6,039
Lycoming	4,354	12,035	23,038	146,721
McKean	480	2,948	232	1,077
Mercer	7,682	18,522	1,828	10,295
Mifflin	12,063	19,841	23,060	318,377
Monroe	89	930	87	1,494
Montgomery	887	3,059	3,956	17,517
Montour	1,680	5,115	844	1,143,807
Northampton	1,750	3,633	340	3,745
Northumberland	4,832	17,753	31,065	1,512,884
Perry	9,933	21,309	59,420	1,173,242
Philadelphia	—	—	22	—
Pike	—	—	—	878
Potter	5,813	8,313	375	2,156
Schuylkill	3,284	9,369	18,081	2,674,294
Snyder	5,992	17,898	55,733	3,965,959
Somerset	16,793	27,890	4,586	12,560
Sullivan	1,935	2,441	68	1,483
Susquehanna	7,266	19,770	372	3,939
Tioga	10,234	18,197	40,154	9,683
Union	8,389	16,388	29,939	2,239,313
Venango	1,329	4,621	424	4,394
Warren	3,712	6,649	406	3,262
Washington	2,269	21,518	541	6,800
Wayne	4,653	8,868	384	6,769
Westmoreland	4,664	19,482	1,085	11,496

County	Milk Cows	Beef Cattle	Hogs & Pigs	Poultry
Wyoming	1,526	4,846	189	1,904
York	8,287	29,592	40,316	1,297,633

Source: Calculated from U.S. Census of Agriculture, 2007, 2012, and 2017

The maps and table above document the concentration of livestock inventories and production in southeastern Pennsylvania, especially Lancaster County. During 2007-2017 Lancaster County's share of Pennsylvania livestock inventory totals were 20% for milk cows, 15% for beef cattle, 29% for hogs and pigs, and 40% for poultry.

3. Pennsylvania Livestock Industry Futures

The Pennsylvania livestock industry has changed dramatically during the last 30 years and will probably change in major ways between now and 2050 regardless of whether climate change is large or small. Climate change impacts on the livestock industry are likely to occur simultaneously with, and interact with, a host of other developments. This section outlines some of the major forces in addition to climate change that may impact the Pennsylvania livestock industry during the next three decades.

3.1. Markets and Consumer Demand

Pennsylvania is part of local, regional, national, and global markets for livestock products. In some cases, such as dairy products, prices are determined on national and global markets, but Pennsylvania is a large enough producer of these products that changes in supply within the state have a noticeable impact on markets. In other cases, such as beef, Pennsylvania has such a small share of national and global markets that what happens within the state has no significant impact on market prices.

Nationally and globally, markets for meat and dairy alternatives are currently small relative to markets for animal-based meat and dairy products, but they are growing quickly. Meat alternatives include products made from tofu, textured vegetable protein, pea protein, and other ingredients, while well-known dairy alternatives include soymilk and almond milk. The global dairy alternatives market is projected to grow about 17% annually between 2019 and 2025 (Grand View Research, 2019), while the global meat alternatives market is projected to grow about 8% annually between 2018 and 2025 (Allied Market Research, 2018).

Cultured meat and synthetic dairy ("lab-grown") products are in the early stages of research and development, but they could become major disrupters to the livestock industry by 2050. For this to occur, a number of issues would have to be resolved, including technical challenges to producing these products at low cost and at scale, concerns about consumer acceptance, and developing appropriate food quality and safety regulations (Stephens et al., 2018; von Massow and Gingerich, 2019).

Even as meat and dairy alternatives are becoming more popular in the U.S., global markets for meat and dairy products are growing due to demand growth in China, India, and other emerging market countries. As incomes increase in these countries, consumers are adding more animal protein to their diets (Chen and Abler, 2014). Global meat consumption and dairy products consumption are both projected to grow by about two-thirds between 2010 and 2050 (Revell, 2015).

Another trend with the potential to transform the livestock industry by 2050 is growing consumer demand for animal welfare and/or sustainability, including access to pasture, space and comfort for confined animals, livestock health, humane slaughter, and a smaller ecological footprint (Ortega and Wolf, 2018; Clark et al, 2017; Caracciolo et al., 2016). The result could be a bifurcation of the livestock industry between the "few, large, concentrated, intensive" supply chain model of today, for consumers unwilling to pay much of a premium for animal welfare or sustainability, and a less intensive supply chain model for consumers who are willing to pay.

3.2. Livestock Industry Structure and Technology

Economies of scale and new livestock production technologies have led to a transformation of the U.S. livestock industry during the past few decades (MacDonald and McBride, 2009). Advances in animal breeding, genetics, genomics, and disease control have improved meat and dairy yields, increased feed use efficiency, and for chicken significantly reduced the number of days to full growth. Projections to 2030 by Wirsenius, Azar, and Berndes (2010) envision continued increases in livestock productivity. At the same time, concerns among consumers and policymakers about antimicrobial resistance, animal welfare, and environmental impacts of large-scale confined feeding operations have grown.

3.3. Environmental Policies

Another trend that may affect Pennsylvania livestock production in coming decades is environmental regulation, particularly with regard to the Chesapeake Bay. The Chesapeake Bay is one of the most valuable natural resources in the United States, but human activity within the Chesapeake Bay watershed has had serious impacts on this ecologically rich area. Soil erosion and nutrient runoff from crop and livestock production have played major roles in the decline of water quality in the Bay. The Chesapeake Bay watershed includes Lancaster County and several other Pennsylvania counties in the southeast and central parts of the state that have significant agricultural production.

Most, but not all, studies of environmental regulations and livestock production in the U.S. have concluded that these regulations impact livestock industry location decisions. For example, Sneeringer (2011) found that more stringent environmental regulations in Southern California led to additional growth in the dairy industry in California's Central Valley, where regulations were weaker, above and beyond the growth in the Central Valley that was occurring anyway for other reasons. Sneeringer (2011) also found that the loss in milk cows from Southern California was larger than the gain in the Central Valley, suggesting that environmental regulation caused some dairy production to move out of California.

4. Climate Change and Pennsylvania Livestock

4.1. Direct Impacts on Livestock Production

The *2015 Pennsylvania Climate Impacts Assessment Update* (Shortle et al., 2015) examined the direct impacts of climate change on livestock yields and production costs in Pennsylvania. Recent reviews of the literature on climate change and livestock by Hristov et al. (2018) and Rojas-Downing et al. (2017) cover similar ground, although those reviews are not specific to Pennsylvania.

Direct impacts include changes in forage productivity, protein content, and digestibility; changes in on-farm feed grain yields and quality; changes in prices of purchased feeds; heat stress and its impacts on livestock productivity and fertility; maintenance costs for livestock during periods of cold weather; for livestock housed indoors, changes in heating, cooling, and ventilation costs; and changes in livestock parasites, pathogens, and disease vectors. Some of these changes may reduce Pennsylvania livestock yields and increase production costs; others may work in the opposite direction.

The literature on the direct impacts of climate change on livestock production continues to advance, but it has not advanced enough in the four years since the *2015 Pennsylvania Climate Impacts Assessment Update* to warrant revisiting this topic. Instead, this report examines the potential indirect impacts on Pennsylvania through livestock industry location decisions.

4.2. Indirect Impacts on Livestock Industry Location

A large portion of U.S. poultry and hog production is currently concentrated in warmer, more southern states. A variety of factors contributed to the historical development of poultry and hog production in the southern U.S., including a relatively favorable (at the time) year-round climate, low labor and land costs compared to other regions of the U.S., improvements in transportation infrastructure, development of national supply chains for livestock products, and favorable state and local tax and regulatory climates. Once established, additional impetus for growth in poultry and hog production in the southern U.S. came from a clustering effect known as agglomeration economies, which refer to the benefits in terms of proximity to suppliers, workers, and customers that businesses in an industry obtain by locating close to each other. Agglomeration economies also include the tendency for businesses in an industry that are close to each other to observe, learn, and copy ideas from each other.

Most poultry and hog production takes place indoors, meaning that climate control is a substantial input into the growth of these livestock. Climate change may increase costs of climate control in southern states, stimulating a movement of poultry and hog production northward into states like Pennsylvania.

In Pennsylvania dairy and beef cattle production, livestock are outdoors much of the time. Dairy cows prefer cool temperatures, with the optimum temperature range for milk production being roughly 40-75°F (Wolfe et al., 2008). There may be a northward movement of dairy production in response to climate change, but a large-scale movement from southern states into Pennsylvania is not possible simply because there is relatively little dairy production in southern states to move. Also, much of the dairy industry in the southern U.S. is located in Florida and

Texas, where it exists to serve local markets in those two states and will likely continue doing so. Instead, a northward movement of dairy production out of Pennsylvania and into New York and the New England states may be more likely.

Beef cattle have a somewhat greater tolerance than dairy cows for heat, but large increases in summer temperatures could place heat stress on them as well. Beef cattle differ from other livestock in that they are geographically dispersed throughout the U.S. They tend to be concentrated in the Midwest, close to major feed grain-producing areas, but they can still be found in large numbers in all 48 contiguous states. Some beef cattle production in southern states could move into Pennsylvania due to climate change, and at the same time some production in Pennsylvania could move to more northern states.

5. Methodology

To our knowledge there are no existing studies that statistically analyze and attempt to quantify the potential impacts of climate change on livestock industry location decisions in Pennsylvania or the U.S. We therefore carried out statistical analyses as part of our work on this report. The data, methodology, and results of these analyses are described in the Appendix to this report. What follows here is a non-technical summary.

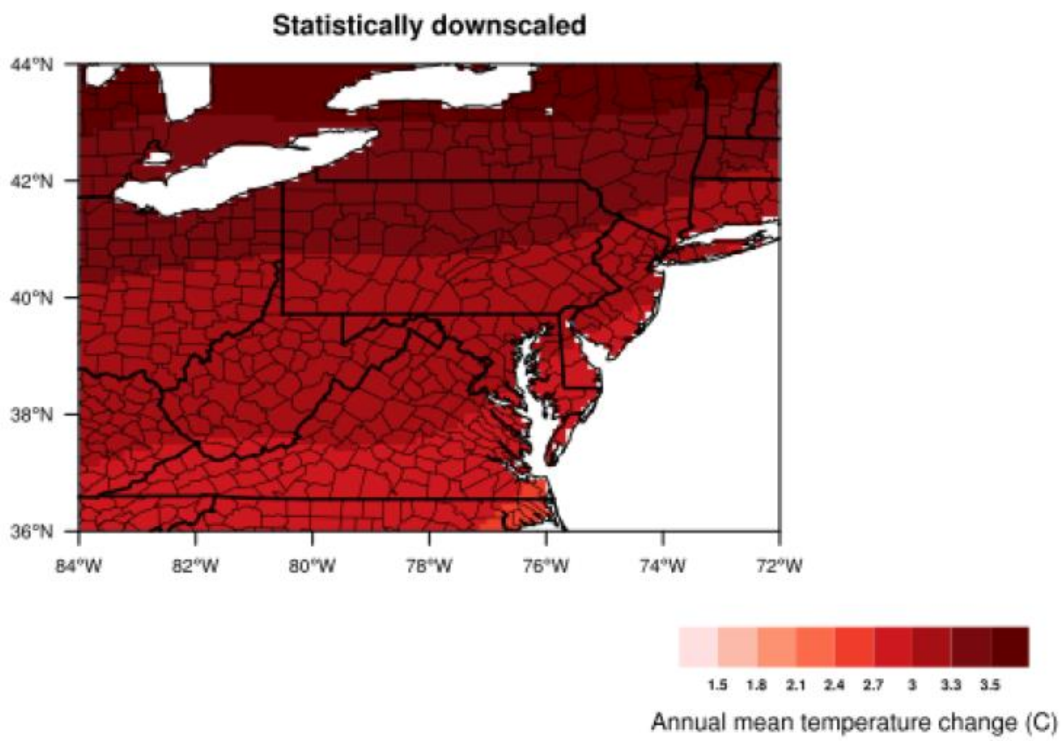
This report uses a "climate analogue" methodology to examine how climate change could impact livestock inventories in Pennsylvania. There are no data for Pennsylvania on how livestock producers would adjust their inventories in response to a future climate because Pennsylvania's future climate is projected to be quite different from any climate in Pennsylvania's history. Instead, we analyze livestock inventories in other parts in the U.S. that currently have a climate similar to Pennsylvania's projected future climate. We do this statistically, using county-level data for the 48 contiguous states, while controlling for other (non-climate) factors impacting livestock inventories in each county. We examine inventories of dairy cows, beef cattle, hogs and pigs, and poultry.

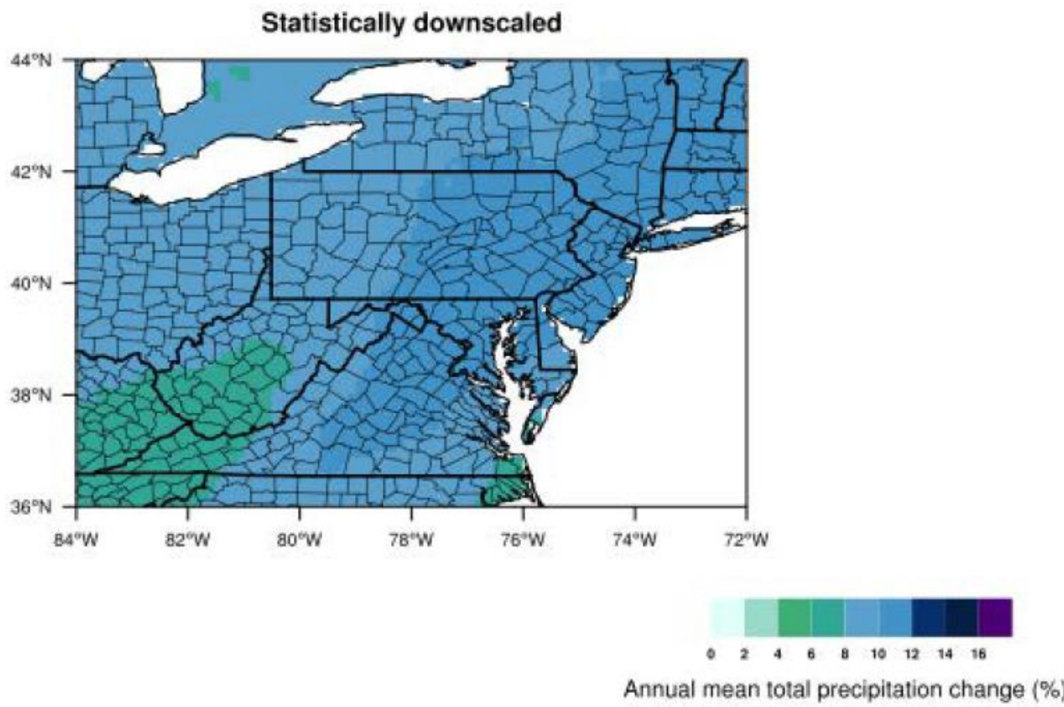
There may have been individual months or years in Pennsylvania's history when the weather was close to the projected future climate, but a distinction needs to be made between the weather and climate. Weather refers to short-term atmospheric conditions, whereas climate is what the weather is like when averaged over a long period of time. Unusual weather is often unanticipated and, when it occurs, agricultural producers have few options for making adjustments. With climate, on the other hand, producers have time to anticipate, learn, and adapt. The *2015 Pennsylvania Climate Impacts Assessment Update* (Shortle et al., 2015) described a number of options available to agriculture in Pennsylvania for adapting to climate change.

The methodology here is somewhat similar to what is called the Ricardian approach in the climate change literature (Mendelsohn and Dinar, 2009). The Ricardian approach uses county-level data (or data for other geographic units) to analyze the impacts of climate change on agricultural land values or net revenues. It assumes that the value of a parcel of land capitalizes the discounted value of all future profits or rents that can be derived from the land, and that these profits or rents may be impacted by changes in temperature and precipitation. One limitation of the Ricardian approach is that it assumes no changes in prices as a result of climate change that could cause the agricultural sector as a whole to expand or contract (Cline, 1996). We address this limitation by incorporating into our projections an expansion in Pennsylvania's livestock sector in response to higher livestock prices anticipated as a result of climate change.

We combine our statistical results on the impacts of climate on livestock inventories with county-level projections of Pennsylvania's future climate in order to project changes in livestock inventories due to climate change. The climate change projections are derived from the statistically downscaled projections for the mid-century period (2041-2070) in the *2015 Pennsylvania Climate Impacts Assessment Update*. These statistically downscaled projections are based on the RCP (Representative Concentration Pathway) 8.5 emissions scenario, which assumes that greenhouse gas emissions continue to grow at a high rate throughout the 21st Century. If the rate of growth in emissions were to slow down, projected climate changes would be smaller.

The figures below show the projections for changes in annual mean temperature (in °C) between an historical period (1971-2000) and mid-century period (2041-2070), and projections for changes in annual total precipitation (in percent) between these two time periods. Every county in Pennsylvania is projected to be warmer and wetter, with somewhat more warming in the northern counties than the southern ones, and a somewhat greater percentage increase in precipitation in the eastern counties than the western ones.





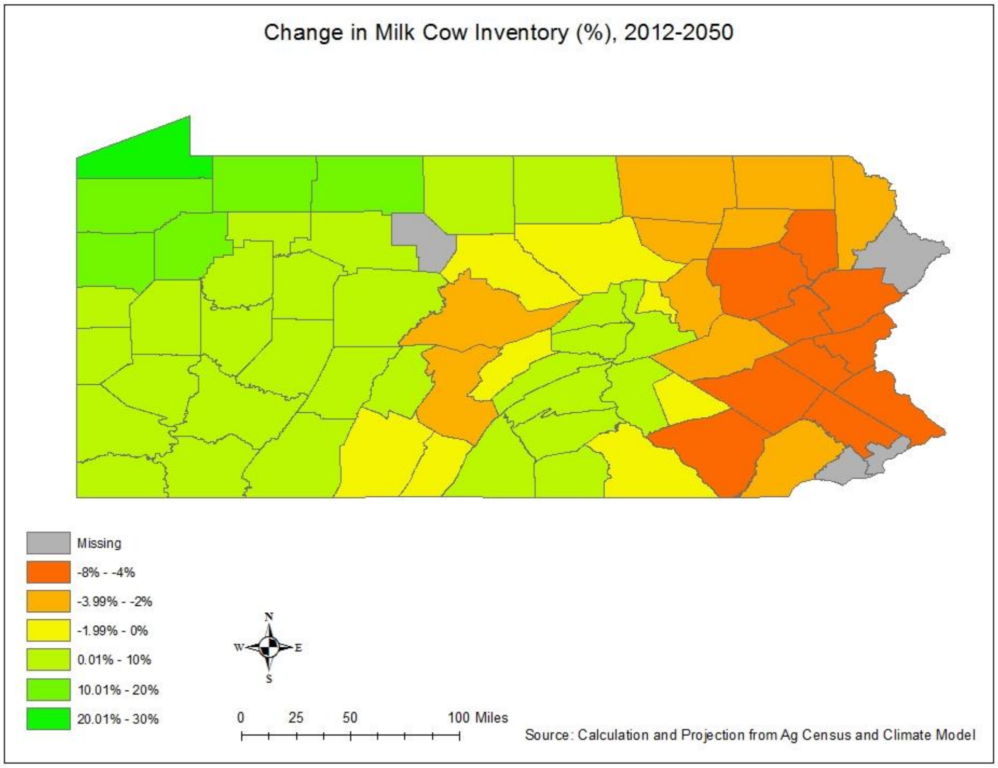
We use the projected changes in livestock inventories under climate change to make projections of changes in nitrogen and phosphorus generated by livestock production. These nutrient projections rely on estimates for common livestock species from the American Society of Agricultural Engineers (2005) of nutrient production per animal per day. A caveat on the nutrient projections is that they assume no improvements between now and 2050 in nutrient uptake efficiency by livestock. For example, feed phytase, which was introduced in the late 1980s, is now widely used by poultry and pork producers around the world to improve nutrient uptake and reduce phosphorus excretion in manure.

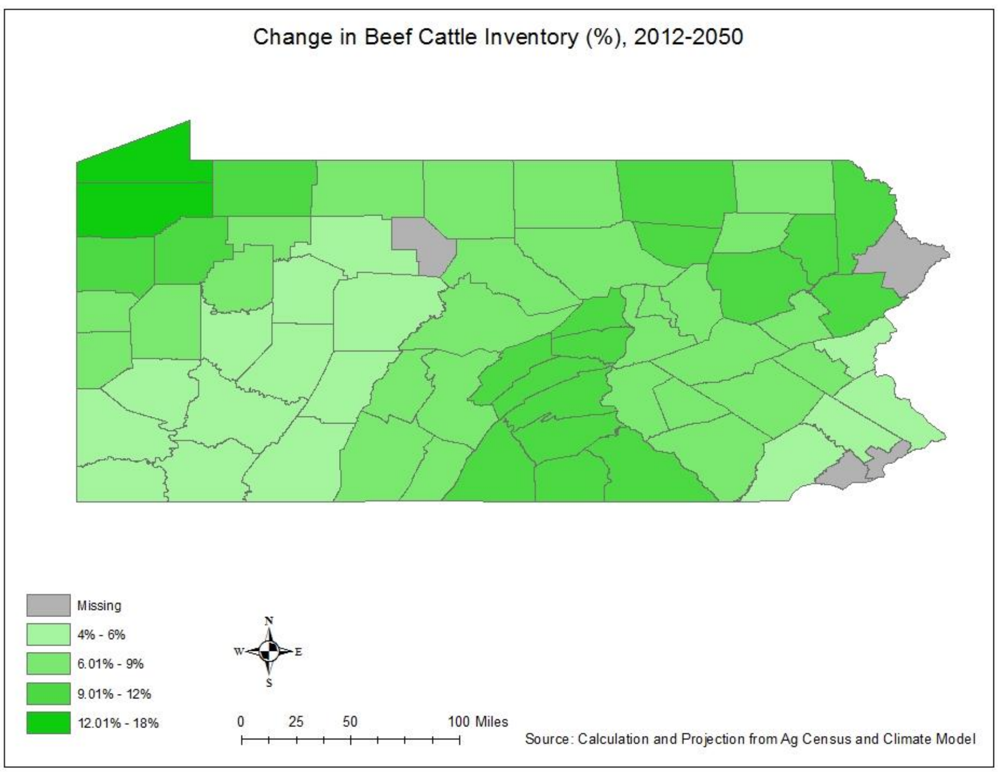
6. Livestock Inventory and Nutrient Projections

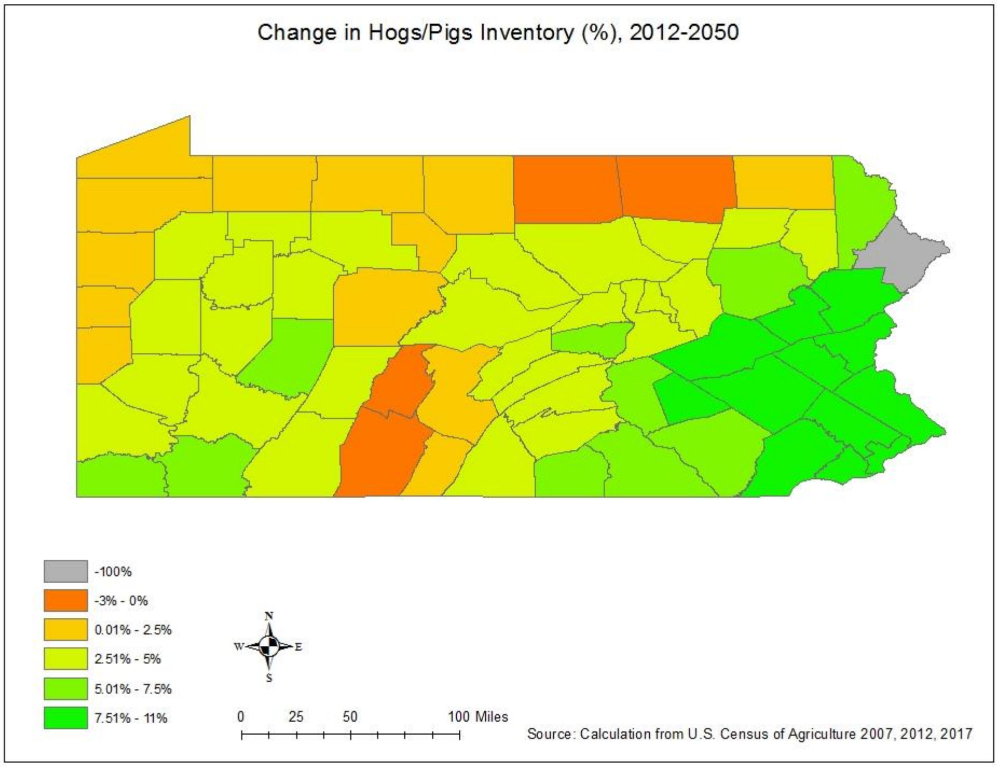
This section reports our projections for 2050 of the potential impacts of climate change on the size of the livestock industry in Pennsylvania. It also reports projections for 2050 of potential impacts of climate change on nutrients (nitrogen and phosphorus) from livestock production. These projections are not predictions or forecasts, nor are they projections of the Pennsylvania livestock industry in 2050. As discussed above, the Pennsylvania livestock industry is likely to change substantially between now and 2050 regardless of whether climate change is large or small. The projections here are solely for changes that may occur as a result of climate change.

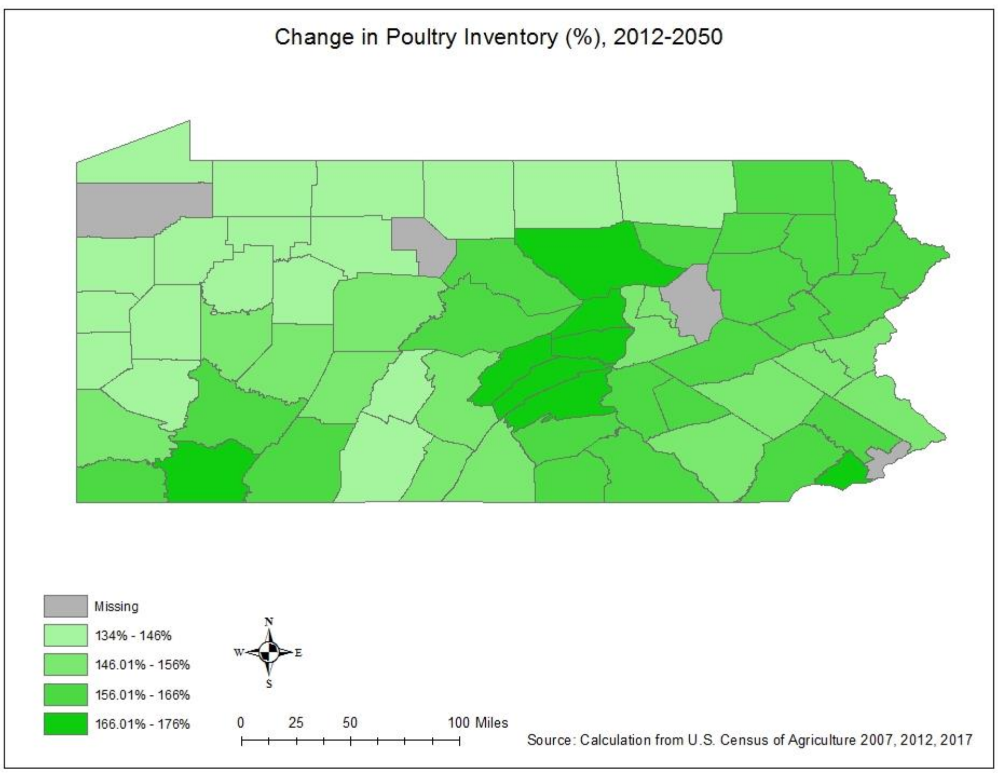
6.1. Livestock Inventory Projections

The maps and table below show projected percentage changes across counties in Pennsylvania of inventories of milk cows, beef cattle, hogs and pigs, and poultry between 2012 and 2050 due to climate change.


Change in Milk Cow Inventory (%), 2012-2050
Missing
-8% - -4%
-3.99% - -2%
-1.99% - 0%
0.01% - 10%
10.01% - 20%
20.01% - 30%
N
W
E
S
0 25 50 100 Miles
Source: Calculation and Projection from Ag Census and Climate Model


Change in Beef Cattle Inventory (%), 2012-2050
Missing
4% - 6%
6.01% - 9%
9.01% - 12%
12.01% - 18%
N
W
E
S
0 25 50 100 Miles
Source: Calculation and Projection from Ag Census and Climate Model


Change in Hogs/Pigs Inventory (%), 2012-2050
-100%
-3% - 0%
0.01% - 2.5%
2.51% - 5%
5.01% - 7.5%
7.51% - 11%
N
W
E
S
0 25 50 100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017


Change in Poultry Inventory (%), 2012-2050
Missing
134% - 146%
146.01% - 156%
156.01% - 166%
166.01% - 176%
N
W
E
S
0 25 50 100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017

Projected Changes in Livestock Inventories by County between 2012 and 2050

County	Milk Cows	Beef Cattle	Hogs & Pigs	Poultry
Adams	2.3%	10.5%	5.5%	165.3%
Allegheny	4.1%	5.5%	3.1%	141.5%
Armstrong	2.3%	5.0%	4.3%	147.6%
Beaver	4.4%	6.0%	1.9%	137.9%
Bedford	-0.6%	6.0%	-0.1%	141.6%
Berks	-4.2%	6.2%	8.7%	152.5%
Blair	0.2%	6.0%	0.0%	141.2%
Bradford	-3.2%	10.4%	-3.0%	139.7%
Bucks	-7.8%	3.6%	9.3%	154.3%
Butler	4.2%	6.7%	2.8%	140.9%
Cambria	2.5%	3.7%	3.6%	153.1%
Cameron	—	—	1.6%	—
Carbon	-4.8%	8.8%	10.8%	159.5%
Centre	-2.5%	7.3%	3.2%	160.7%
Chester	-3.4%	5.7%	10.3%	163.4%
Clarion	6.4%	6.1%	4.5%	145.7%
Clearfield	1.5%	5.8%	1.8%	149.2%
Clinton	-1.7%	6.9%	3.1%	160.0%
Columbia	-3.7%	8.6%	4.9%	—
Crawford	19.8%	14.0%	1.1%	—
Cumberland	1.4%	11.5%	3.7%	164.1%
Dauphin	0.3%	8.3%	7.1%	163.4%
Delaware	—	—	9.5%	167.6%
Elk	4.8%	5.6%	3.4%	143.4%
Erie	29.9%	17.4%	1.0%	134.4%
Fayette	3.2%	4.5%	5.9%	169.9%
Forest	7.1%	7.6%	3.7%	142.4%
Franklin	0.8%	10.3%	3.5%	152.7%
Fulton	-1.5%	8.2%	1.2%	149.2%
Greene	4.1%	3.8%	6.2%	160.7%
Huntingdon	-2.1%	7.2%	1.9%	153.5%
Indiana	5.2%	4.0%	5.7%	155.2%
Jefferson	4.1%	5.8%	3.9%	141.1%
Juniata	1.6%	10.6%	3.5%	171.0%
Lackawanna	-4.6%	9.7%	4.6%	161.8%
Lancaster	-4.1%	7.2%	6.4%	152.2%
Lawrence	5.1%	8.0%	1.2%	138.8%
Lebanon	-1.7%	7.4%	9.0%	163.5%
Lehigh	-5.4%	6.4%	9.5%	155.3%
Luzerne	-4.6%	9.7%	5.1%	161.3%
Lycoming	-1.4%	9.0%	3.5%	166.3%
McKean	10.8%	8.3%	2.0%	140.1%
Mercer	11.6%	11.8%	1.2%	143.6%

County	Milk Cows	Beef Cattle	Hogs & Pigs	Poultry
Mifflin	-0.2%	9.5%	3.3%	166.2%
Monroe	-4.6%	10.7%	9.2%	163.5%
Montgomery	-5.6%	5.6%	9.2%	156.9%
Montour	-1.6%	8.7%	3.4%	153.9%
Northampton	-6.4%	5.5%	9.0%	154.5%
Northumberland	0.9%	8.8%	4.4%	154.1%
Perry	2.7%	11.7%	4.0%	169.4%
Philadelphia	—	—	8.6%	—
Pike	—	—	—	160.0%
Potter	5.6%	6.2%	1.3%	142.3%
Schuylkill	-2.1%	8.7%	10.0%	161.8%
Snyder	4.6%	10.4%	5.8%	175.1%
Somerset	3.1%	4.7%	4.3%	161.2%
Sullivan	-3.4%	10.0%	4.6%	165.4%
Susquehanna	-3.6%	8.3%	2.2%	156.8%
Tioga	0.2%	8.0%	-0.8%	136.5%
Union	0.5%	9.3%	4.5%	173.8%
Venango	10.4%	9.4%	3.1%	144.7%
Warren	15.7%	10.5%	2.3%	140.0%
Washington	3.1%	3.8%	4.4%	149.9%
Wayne	-2.9%	9.1%	5.7%	159.0%
Westmoreland	3.0%	3.7%	4.8%	156.0%
Wyoming	-3.8%	8.3%	2.6%	161.8%
York	-0.1%	9.4%	5.3%	158.6%

The four types of livestock show distinct patterns of projected change. For milk cows, inventories in the southeast counties that are currently the heart of Pennsylvania's dairy industry are projected to decline. On the other hand, inventories in the northwest counties, where dairy is currently unimportant, are projected to rise. Crawford and Erie counties are projected to increase by 20% and 30%, respectively. For Pennsylvania as a whole, there is virtually no projected change (0%) in milk cow inventories between 2012 and 2050. This suggests that climate change may lead a spatial rearranging of the dairy industry within Pennsylvania but no large-scale movement northward to New York or the New England states.

For beef cattle, inventories are projected to increase modestly throughout Pennsylvania, with the largest percentage increases in the northwest counties. Crawford and Erie counties, which currently account for only about 3% of Pennsylvania beef cattle inventories, are projected to grow by about 15%. For Pennsylvania as a whole, beef cow inventories are projected to rise by about 8%. This suggests that climate change may lead to a small northward movement of the beef industry into Pennsylvania.

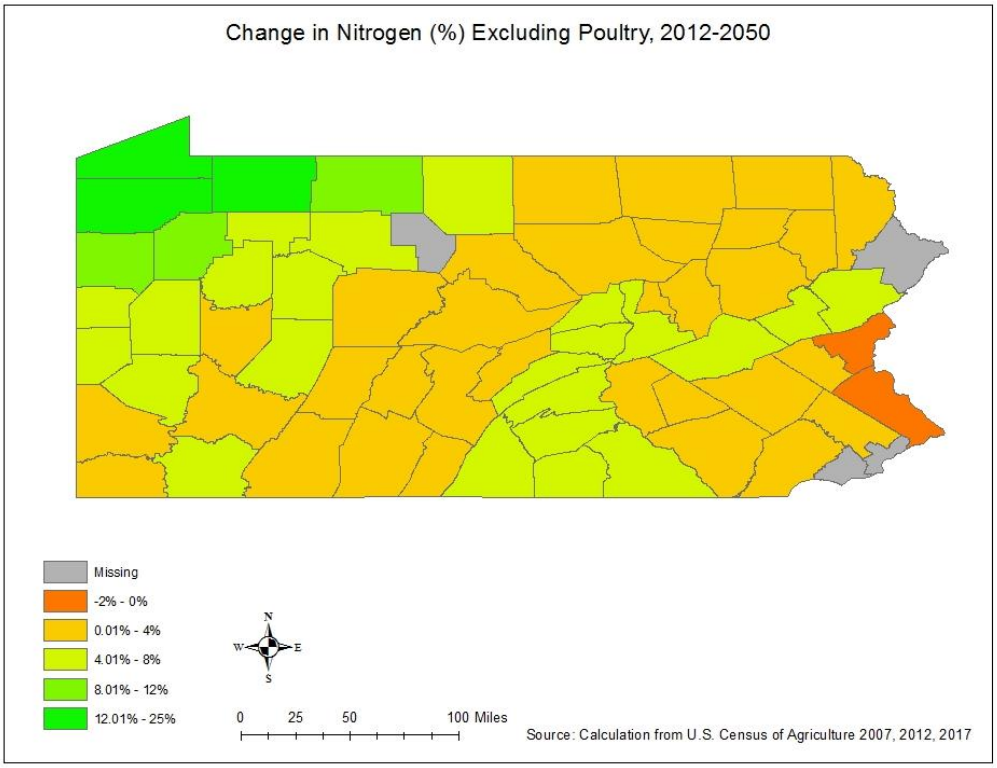
For hogs and pigs, the projected spatial pattern of change in inventories is almost opposite to milk cows and beef cattle. The largest percentage increases in hog/pig inventories are in the southeastern counties, while the smallest increases or declines are in the northern and northwest counties. Bedford and Blair counties are also projected to decline, but the declines in those two counties are negligible (less than 0.1%). The industry is currently concentrated in south-central and southeastern Pennsylvania, so that the projected growth in southeastern counties is consistent with clustering as a result of agglomeration economies. For Pennsylvania as a whole, hog/pig inventories are projected to increase by about 5% between 2012 and 2050. Similar to beef cattle, this suggests that climate change may lead to a small northward movement of the hog/pig industry into Pennsylvania.

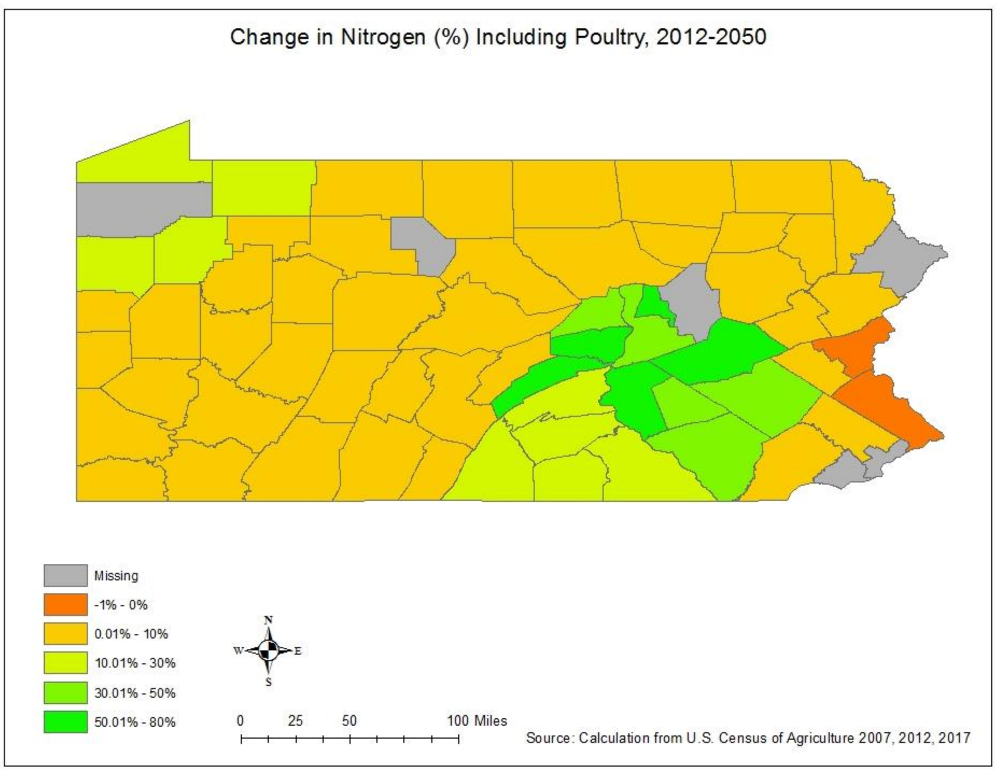
The projections for poultry show increases in inventories throughout Pennsylvania, but they are much larger in percentage terms than increases for the other types of livestock. The increases range from 134% (Erie County) to 175% (Snyder County), with an average for Pennsylvania as a whole of 158%. The largest percentage increases are in south-central Pennsylvania, and the industry is currently concentrated in south-central and southeastern Pennsylvania. That is consistent with clustering as a result of agglomeration economies; however, the sizable percentage increases in other parts of the state are not consistent with clustering. Thirty-two of Pennsylvania's 67 counties currently have poultry inventories of less than 10,000 (compared to an average county inventory for Pennsylvania as a whole of 907,000), and the projected percentage increases in these counties range from 136% to 170%.

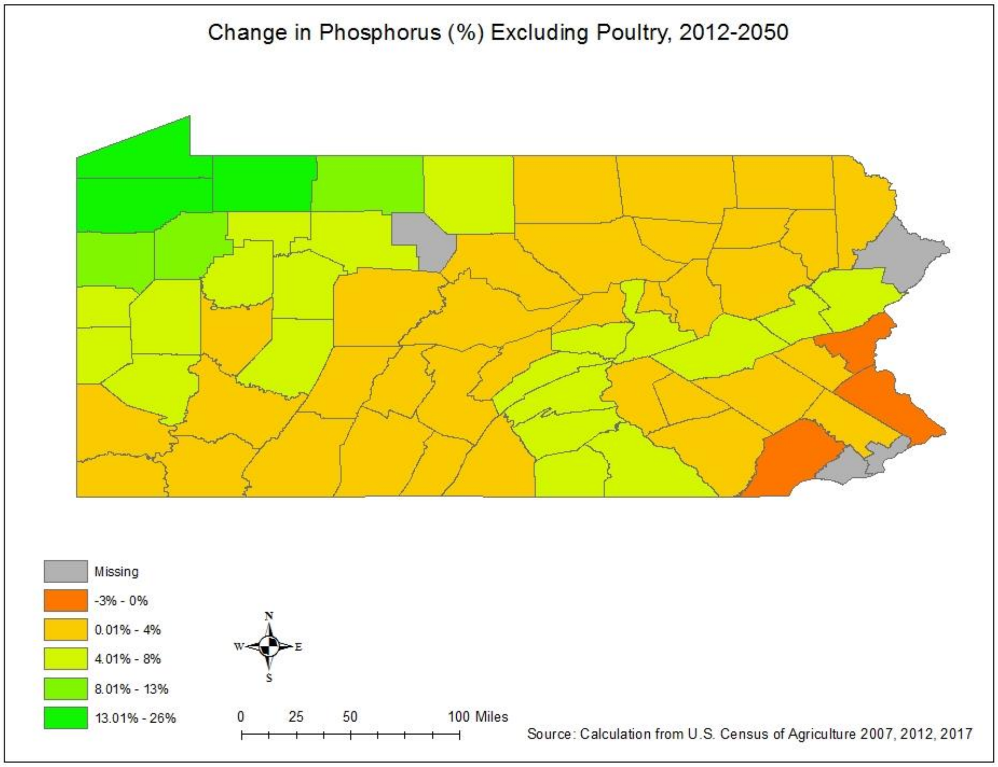
It is not implausible that Pennsylvania's poultry industry could more than double in size over the 38-year period 2012 to 2050 due to climate change, but it does seem implausible that the growth would be spread so evenly across counties. Given the highly clustered nature of the poultry industry, one would expect the vast majority of growth to occur in south-central and southeastern Pennsylvania, where the industry is currently concentrated. The statistical models for poultry estimated for this report appear to have difficulty in capturing the high degree of clustering in this industry.

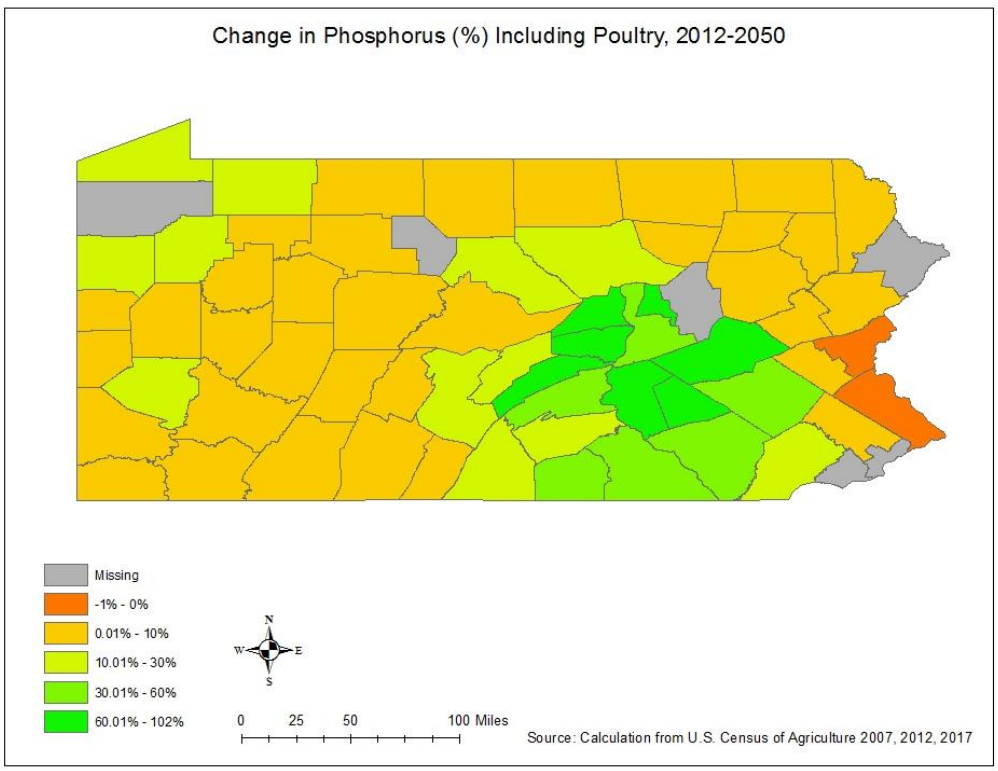
6.2. Nutrient Projections

The maps and table below show projected percentage changes across counties in Pennsylvania in nitrogen and phosphorus in animal manure between 2012 and 2050 due to climate change. Because of the questions about the county-level projections for poultry, there are two sets of maps: one including nutrients from milk cows, beef cattle, and hogs/pigs but not poultry; and the other including all four livestock types.


Change in Nitrogen (%) Excluding Poultry, 2012-2050
Missing
-2% - 0%
0.01% - 4%
4.01% - 8%
8.01% - 12%
12.01% - 25%
N
W
E
S
0
25
50
100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017


Change in Nitrogen (%) Including Poultry, 2012-2050
Missing
-1% - 0%
0.01% - 10%
10.01% - 30%
30.01% - 50%
50.01% - 80%
N
W
E
S
0
25
50
100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017


Change in Phosphorus (%) Excluding Poultry, 2012-2050
Missing
-3% - 0%
0.01% - 4%
4.01% - 8%
8.01% - 13%
13.01% - 26%
N
W
E
S
0
25
50
100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017


Change in Phosphorus (%) Including Poultry, 2012-2050
Missing
-1% - 0%
0.01% - 10%
10.01% - 30%
30.01% - 60%
60.01% - 102%
N
W
E
S
0
25
50
100 Miles
Source: Calculation from U.S. Census of Agriculture 2007, 2012, 2017

Projected Changes in Nutrients from Livestock by County between 2012 and 2050

County	Nitrogen		Phosphorus	
	Excluding Poultry	Including Poultry	Excluding Poultry	Including Poultry
Adams	6%	22%	6%	34%
Allegheny	5%	9%	5%	13%
Armstrong	4%	4%	4%	4%
Beaver	5%	6%	5%	6%
Bedford	2%	4%	2%	5%
Berks	1%	32%	1%	50%
Blair	2%	2%	2%	2%
Bradford	2%	2%	1%	1%
Bucks	-2%	-1%	-3%	0%
Butler	6%	6%	6%	6%
Cambria	3%	3%	3%	4%
Cameron	—	—	—	—
Carbon	6%	8%	6%	8%
Centre	1%	3%	1%	3%
Chester	0%	9%	0%	16%
Clarion	6%	6%	6%	7%
Clearfield	4%	4%	4%	4%
Clinton	3%	8%	2%	13%
Columbia	2%	—	2%	—
Crawford	17%	—	18%	—
Cumberland	6%	19%	5%	28%
Dauphin	4%	59%	3%	83%
Delaware	—	—	—	—
Elk	5%	7%	5%	8%
Erie	24%	25%	25%	26%
Fayette	4%	4%	4%	5%
Forest	7%	8%	7%	8%
Franklin	4%	16%	4%	24%
Fulton	3%	3%	2%	2%
Greene	4%	4%	4%	4%
Huntingdon	2%	8%	1%	13%
Indiana	5%	5%	5%	5%
Jefferson	5%	5%	5%	5%
Juniata	5%	54%	4%	78%
Lackawanna	2%	6%	1%	8%
Lancaster	1%	38%	0%	58%
Lawrence	6%	7%	6%	7%
Lebanon	3%	46%	3%	67%
Lehigh	1%	3%	0%	4%
Luzerne	4%	5%	3%	6%
Lycoming	4%	9%	3%	14%
McKean	9%	9%	9%	10%

County	Nitrogen		Phosphorus	
	Excluding Poultry	Including Poultry	Excluding Poultry	Including Poultry
Mercer	12%	12%	12%	12%
Mifflin	4%	10%	3%	14%
Monroe	8%	9%	7%	10%
Montgomery	2%	5%	1%	7%
Montour	4%	72%	3%	97%
Northampton	-1%	0%	-2%	-1%
Northumberland	5%	38%	5%	58%
Perry	6%	25%	6%	39%
Philadelphia	—	—	—	—
Pike	—	—	—	—
Potter	6%	6%	6%	6%
Schuylkill	5%	77%	4%	102%
Snyder	7%	70%	7%	96%
Somerset	4%	4%	4%	4%
Sullivan	1%	1%	0%	1%
Susquehanna	2%	3%	2%	2%
Tioga	3%	3%	2%	2%
Union	4%	48%	4%	71%
Venango	10%	10%	10%	11%
Warren	13%	14%	14%	14%
Washington	4%	4%	4%	4%
Wayne	2%	3%	1%	2%
Westmoreland	3%	4%	3%	4%
Wyoming	3%	3%	2%	2%
York	5%	25%	5%	40%

Comparing the maps/table with and without nutrients from poultry, it is clear that the large projected increases in poultry inventories are driving most of the county-level increases in nutrients when poultry is included. Only two counties, Bucks and Northampton, show decreases in nitrogen and phosphorus both including and excluding poultry. Chester County shows a decrease in phosphorus when poultry is excluded. These decreases in nutrients are a result of declines in milk cow inventories in these three counties.

When poultry is included, the counties with the largest percentage increases in nitrogen and phosphorus all lie in the Susquehanna River Basin and/or Delaware River Basin. Schuylkill County, which lies partly in both of these river basins, shows the greatest increases, 77% for nitrogen and 102% for phosphorus. When poultry is excluded, Erie county shows the greatest increases, 24% for nitrogen and 25% for phosphorus.

When poultry is included, the county with the largest physical increases in nutrients is Lancaster County, about 94,000 additional pounds per day of nitrogen and 27,000 additional pounds per day of phosphorus. When poultry is excluded, the counties with the largest physical increases in nutrients are Franklin County for nitrogen (about 3,500 additional pounds per day) and Crawford County for phosphorus (about 500 additional pounds per day).

7. Conclusions

The projections in this report suggest that climate change could lead to significant changes in the product composition and spatial distribution of Pennsylvania's livestock industry between 2012 and 2050. Climate change could cause Pennsylvania's poultry inventory to more than double in size. Much smaller, but still positive, increases in inventory could occur for beef cattle and hogs and pigs. The projected impact of climate change of dairy inventory for Pennsylvania as a whole is about zero. Relatively speaking, this means that poultry's share of Pennsylvania's livestock industry would increase while dairy's share would decline.

The projections in this report indicate that climate change could lead to a spatial rearranging of the dairy industry within Pennsylvania. Milk cow inventories in southeast counties that are currently the heart of Pennsylvania's dairy industry are projected to decline, while inventories in northwest counties are projected to rise. For beef cattle, inventories are projected to increase modestly throughout Pennsylvania, with the largest percentage increases in the northwest counties. On the other hand, the largest projected percentage increases in hog/pig inventories are in the southeastern counties, while the smallest increases or declines are in the northern and northwest counties.

Projected changes in nitrogen and phosphorus in animal manure between 2012 and 2050 due to climate change show increases throughout almost all of Pennsylvania, regardless of whether or not nutrients from poultry are included in the calculations. These changes could exacerbate current water quality concerns with excess nutrients in livestock manure, especially in the Susquehanna and Delaware River Basins.

Appendix

This Appendix describes the statistical models, data, and estimation results of statistical analyses on the impacts of climate on livestock inventories, controlling for other relevant variables that affect inventories. This Appendix also contains details on the projections of the impacts of climate change on livestock inventories and nitrogen and phosphorus generated by livestock production.

A.1. Statistical Models

The statistical models in this report are regression models run on county-level data for the 48 contiguous U.S. states in which the dependent variable is the natural logarithm of 1 plus the county's inventory of a given type of livestock (dairy cows, beef cattle, hogs and pigs, or poultry), $ln(1 + y_{ij})$, where y_{ij} is the level of inventory of livestock type i in county j. Logarithmic transformations are used on the dependent variable and some of the explanatory variables to mitigate against heteroskedasticity. The value 1 is added to the inventory so that the dependent variable is 0 when a county has no inventory. Adding 1 should have no discernible impact on the results because county inventories are typically in the thousands to hundreds of thousands.

Three kinds of regression models are run for each of type of livestock. The first is ordinary least squares (OLS), run on only the counties with a positive level of inventory for a given type of livestock. Results of these regressions should be interpreted as conditional on a county having that type of livestock. The second type of regression model is tobit, run on counties with both zero and positive inventories. Results of the tobit regressions predict both which counties have positive inventories and the levels of inventory among those counties with positive inventories. The third type of model is probit, again run on counties with both zero and positive inventories. Results of the probit regressions predict which counties have positive inventories but do not predict levels of inventory among those counties with positive inventories.

Our projections use the tobit model results because they yield estimates of the impacts of climate variables on both the existence/absence of livestock inventory and the inventory level if inventory is positive. The OLS and probit models were estimated as robustness checks, and results were generally similar to the tobit in terms of signs and levels of statistical significance on the climate variables.

Climate variables included as explanatory variables in the regressions are each county's monthly mean precipitation levels, monthly mean maximum temperatures, monthly standard deviations for precipitation, and monthly standard deviations for maximum temperatures. Means and standard deviations are calculated over a 30-year period, as explained in the Data section below. Combining the means and standard deviations, there are 48 climate variables. Using both permits us to capture climate averages (means) and climate variability (standard deviations).

Other explanatory variables in the regressions are the natural log of a county's land area, the natural log of a county's water area, the natural log of the county's (human) population, and a series of eight dummy variables for farm resource regions of the U.S. (there are nine regions in total, one was excluded as the reference region from the regressions). In total, there are 59 explanatory variables: 48 climate variables, 8 farm resource region variables, and the 3 area and population variables.

Land area is expected to have a positive impact on livestock inventories—the larger the county, the more space for livestock facilities and any associated feed grain production. Water area is expected to have a negative impact on inventories, insofar as it may be an indicator of the potential for flooding of farm fields, farm facilities, and roads.

A county's population could have a positive or negative impact on inventories. A greater population means a larger local market for livestock products, but on the other hand, it also means greater competition for land from housing, retail, and other urban land uses. Supply chains for watery products like fluid milk, ice cream, and chilled meat are typically short because these products have a short shelf life and are expensive to transport over long distances. For these types of products, we would expect the local market effect of a greater population to dominate the competition for land effect, leading to a positive impact of population on inventories. Other kinds of livestock products, like frozen beef, have a long shelf life and can be transported over long distances at an acceptable cost relative to the value of the product. For these types of products, we would expect the competition for land effect to dominate, leading to a negative impact of population on inventories.

A variety of other factors influence livestock location decisions, including proximity to local food processing plants, proximity to sources of livestock feed and other inputs into livestock production, transportation infrastructure (both road and rail), environmental regulations, and property taxes (Abler, Shortle, and Huang, 2018). We do not include these factors as explanatory variables in the regressions because, over the three decades between now and 2050, they are endogenous. If changes in climate dictate changes in livestock location, new processing plants, new suppliers of production inputs, and new road and rail networks to service the new locations could all follow.

One caveat on our methodology is that climate change between now and 2050 could impact three of the explanatory variables included in the regressions: land area, water area, and population. Water area could change due to changes in precipitation, causing land area to also change because land area is total county area minus water area. Population could change as climate amenities change, making some counties more attractive places to live and others less attractive. We do not consider these impacts due to a lack of estimates for Pennsylvania on their direction and magnitude. Of course, population will also be changing due to demographic processes, and the Pennsylvania State Data Center (Behney et al., 2014) has made county-level population projections to 2040. We do not consider those changes here because our focus is solely on livestock inventory changes due to climate change.

Another caveat is that the projections of the impacts of climate change on livestock inventories and nutrients from livestock production assume that the estimated coefficients from the tobit models do not change between now and 2050. In other words, the projections assume that the relationships between the climate variables and livestock inventories remain stable over time. As an illustration of how they might change, suppose that changing consumer demands transform the supply chain model for livestock products from the concentrated and intensive model of today to a less intensive model with a much larger percentage of livestock on pasture. In that case the effects of climate on forage productivity, protein content, and digestibility would become more important than they are today, causing the coefficients on the climate variables to change. We do not consider this because we have no information on what the direction and magnitude of the changes in the coefficients might be.

A.2. Data

Data Sources and Merging Data

For the regression models we compiled county-level climate, livestock inventory, land area, water area, human population, and farm resource region data. The source of climate data is the National Centers for Environmental Information (NCEI) (2019). NCEI provides U.S. data, maps, and rankings for temperature, precipitation, and other climate variables. We accessed the temperature and precipitation datasets through the FTP site ftp://ftp.ncdc.noaa.gov/pub/data/cirs/climdiv/. There are 3,107 counties or county-equivalents across the 48 contiguous states in the NCEI database. County data are available from 1895 through the present, although for this report we used monthly data for the 30-year period 1979-2008 on the average maximum daily temperature and total precipitation. For each county we calculated monthly means and standard deviations for average maximum daily temperature and total precipitation. The result is 48 climate variables: 12 monthly temperature means, 12 monthly precipitation means, 12 monthly temperature standard deviations, and 12 monthly precipitation standard deviations. The temperature data are in °F, while the precipitation data are in inches.

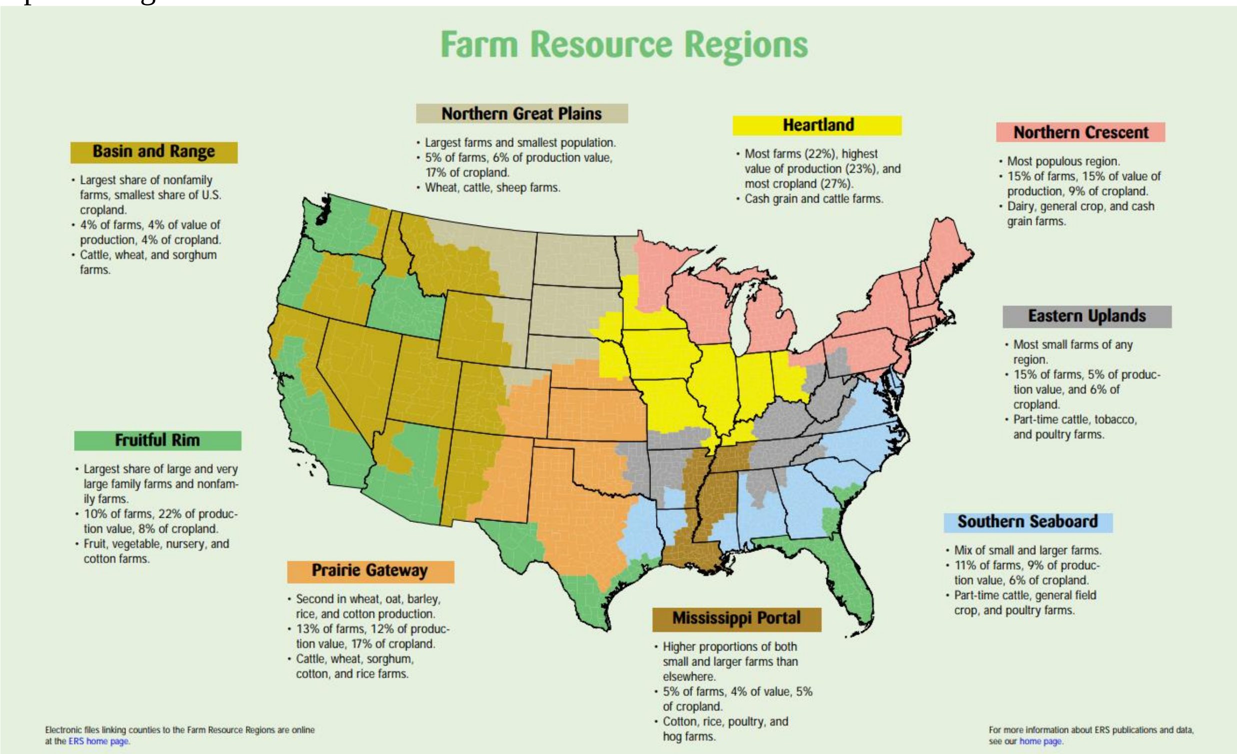
We collected livestock inventory data from the USDA's National Agricultural Statistics Service (NASS). NASS provides two sources of county-level livestock data: producer surveys and the Census of Agriculture. We used both sources of data for this report, running one set of regressions using the producer survey data on livestock inventories and a second set using the Census of Agriculture data. Each source has its advantages and disadvantages, which is why we used both: the surveys provide annual data, whereas the Census is once every five years; the Census is a complete enumeration, whereas the surveys rely on samples of farms. We accessed both sources of data from the NASS Quick Stats website (https://quickstats.nass.usda.gov/).

For the surveys, we used an average for each county of the yearly average inventory for each type of livestock for the time period 2009-2018 (milk cows, beef cattle, and poultry) or 2009-2017 (hogs and pigs). 2018 data on hogs and pigs were not yet available at the time this report was prepared. For the Census, we used averages for each county of inventories from the 2007, 2012, and 2017 Censuses. In both cases, taking an average across years smooths out year-to-year fluctuations in inventories due to ups and downs in livestock product prices, feed costs, energy costs, and other factors.

For the surveys, data were directly available from Quick Stats on inventories of milk cows, beef cattle, hogs, and chickens. For the Census, milk cow and hog/pig inventories were available directly. We define beef cattle inventory as inventory of all cattle and calves minus inventory of milk cows. We define poultry inventory as the sum of inventories of chicken broilers, chicken layers, and chicken pullets.

We collected county-level land area, water area, and population data from the U.S. Census Bureau website (https://www.census.gov/data.html). Population data are number of persons from the 2010 Census of Population. Land area and water area are in square miles.

The farm resource regions are from USDA's Economic Research Service (ERS) (2000). We accessed data on each county's region from the ERS website (https://www.ers.usda.gov/media/9592/reglink.xls). As shown in the figure from ERS on the next page, there are nine regions: Northern Crescent, Heartland, Northern Great Plains, Basin and Range, Eastern Uplands, Fruitful Rim, Prairie Gateway, Mississippi Portal, and Southern Seaboard. Most Pennsylvania counties are in the Northern Crescent region, which was used as the control region in the regressions. Counties in southwest Pennsylvania are in the Eastern Uplands region.



NASS uses FIPS codes to identify a county. The five-digit FIPS codes use the two-digit FIPS state code, followed by the three digits of the county code within the state. County FIPS codes in the U.S. are usually (with a few exceptions) in the same sequence as alphabetized county names within a state. They are usually (but not always) odd numbers so that new or changed county names can be fit in their alphabetical sequence slot. Although identifying a county's livestock inventory using its FIPS code is straightforward; our main challenge in merging data was to match the climate and livestock data because of NCEI's different method for numbering counties. NCEI also uses a five-digit code, which is like FIPS code, to identify a county; however, the first two digits (state code) are different from the standard FIPS state code. So, we manually matched the counties in climate and livestock datasets. We replaced the first two digits of the standard FIPS codes (the state codes) to match with the NCEI's coding method. This is necessary because the NCEI's dataset is more comprehensive in its county coverage than USDA's datasets.

Data Cleaning

Both the producer survey data and Census of Agriculture data on livestock inventories are not complete. A number of counties are excluded from the dataset for each livestock type, and we assumed that the excluded counties had a zero inventory of that type of livestock. A number of other counties have nondisclosed livestock inventory data in order to avoid the risk of disclosing information about individual farms. In addition, the survey data on milk and beef cattle have a number of inventories summed up as “other counties” in the datasets. No information is available regarding which counties these might be. We dropped the counties with nondisclosed livestock inventory information and, for the survey data, also dropped the “other counties” entries from our compiled datasets used to run the OLS, tobit, and probit regressions.

The resulting sample sizes for each livestock type and data source are shown in the table below. The survey figures for poultry are omitted from the table and from the regression model estimations because of the large number of counties dropped due to non-disclosed data, including all 67 counties in Pennsylvania. The survey figures for hogs and pigs are omitted due to an unusually large number of counties (more than 2,000) with zero inventory, which is far larger than the Census figure of 84 counties with zero inventory. The sample size listed in the table is equal to the sum of counties with zero inventory and counties with positive inventory. The number of counties dropped due to non-disclosed data is equal to the 3,107 counties and county-equivalents in the NCEI database minus the sample size.

Sample Information for Each Livestock Type and Data Source

Livestock Type	Data Source	Counties with Zero Inventory	Counties with Positive Inventory	Sample Size	Counties Dropped Due to Non-Disclosed Data
Milk Cows	Survey	822	1,387	2,209	898
	Census	302	2,268	2,570	537
Beef Cattle	Survey	601	2,139	2,740	367
	Census	45	2,513	2,558	549
Hogs and Pigs	Census	84	2,781	2,865	242
Poultry	Census	44	2,268	2,312	795

A.3. Estimation Results

The tables in this section present the tobit model estimation results. The OLS and probit results are not presented in order to save space. As noted above, they were generally consistent with the tobit results. Across the six tobit regressions reported below, about half (34) of the 72 mean monthly precipitation variables are statistically significant, with the estimated coefficients on 19 of the 34 positive and 15 of the 34 negative. By season, with winter being December through February, spring March through May, summer June through August, and fall September through November, more of the estimated coefficients in the 34 cases are positive than negative in winter, summer, and fall, with the opposite being the case in the spring.

About two-thirds (47) of the 72 mean monthly temperature variables are statistically significant, split between 22 whose estimated coefficients are positive and 25 whose estimated coefficients are negative. By season, more estimated coefficients are negative than positive in winter and spring, whereas more are positive than negative in summer and fall.

About half (34) of the 72 monthly precipitation standard deviation variables are statistically significant, with the estimated coefficients on 17 of the 34 positive and 17 of the 34 negative. By season, the positive and negative estimated coefficients are also about evenly split.

A smaller number (30) of the monthly temperature standard deviation variables are statistically significant, with the estimated coefficients on 17 of the 30 being negative and the other 13 positive. By season, there is a split between winter and spring, on the one hand, and summer and fall on the other. In the 17 cases where the winter and spring temperature standard deviation variables are statistically significant, 14 of the estimated coefficients are negative. In the 13 cases where the summer and fall temperature standard deviation variables are statistically significant, 10 of the estimated coefficients are positive.

The signs of the estimated coefficients on the log of land area, the log of water area, and the log of population agree with expectations, and these three variables are statistically significant in almost all cases. The regional dummies are generally statistically significant as well, and their signs are consistent with the present-day spatial distribution of livestock production across the U.S.

Tobit Estimation Results: Milk Cow Inventory, Survey Data

($\chi^2_{(59)}$ = 1345; Pr>χ^2 = 0.000; *pseudo* R^2 = 0.13)

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
ln(Land Area)	1.696	0.183	9.27	0.000	1.337	2.054
ln(Water Area)	-0.324	0.073	-4.41	0.000	-0.468	-0.180
ln(Population)	0.701	0.087	8.04	0.000	0.530	0.872
Mean Precip Jan	0.762	0.697	1.09	0.274	-0.604	2.128
Mean Precip Feb	-0.309	0.836	-0.37	0.712	-1.949	1.332
Mean Precip Mar	-0.241	0.701	-0.34	0.731	-1.615	1.134
Mean Precip Apr	-0.644	0.658	-0.98	0.328	-1.934	0.646
Mean Precip May	-1.940	0.542	-3.58	0.000	-3.003	-0.877
Mean Precip Jun	2.831	0.461	6.15	0.000	1.928	3.734
Mean Precip Jul	-2.970	0.412	-7.21	0.000	-3.778	-2.162
Mean Precip Aug	2.388	0.478	4.99	0.000	1.450	3.326
Mean Precip Sep	-0.425	0.510	-0.83	0.404	-1.425	0.574
Mean Precip Oct	1.160	0.598	1.94	0.053	-0.013	2.334
Mean Precip Nov	-1.462	0.568	-2.57	0.010	-2.576	-0.349
Mean Precip Dec	2.264	0.642	3.52	0.000	1.004	3.524
Mean Temp Jan	-1.399	0.434	-3.22	0.001	-2.250	-0.548
Mean Temp Feb	2.122	0.389	5.45	0.000	1.358	2.885
Mean Temp Mar	-1.404	0.347	-4.04	0.000	-2.084	-0.723
Mean Temp Apr	1.423	0.383	3.72	0.000	0.672	2.175
Mean Temp May	-2.108	0.437	-4.82	0.000	-2.966	-1.250
Mean Temp Jun	2.031	0.397	5.11	0.000	1.252	2.811
Mean Temp Jul	-2.226	0.495	-4.49	0.000	-3.197	-1.255
Mean Temp Aug	1.347	0.460	2.93	0.003	0.444	2.250
Mean Temp Sep	0.538	0.421	1.28	0.201	-0.287	1.363
Mean Temp Oct	-1.016	0.486	-2.09	0.037	-1.970	-0.062
Mean Temp Nov	1.907	0.400	4.76	0.000	1.122	2.693
Mean Temp Dec	-1.412	0.485	-2.91	0.004	-2.363	-0.461

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
Std Dev Precip Jan	-0.651	0.605	-1.08	0.282	-1.838	0.536
Std Dev Precip Feb	1.746	0.729	2.39	0.017	0.316	3.176
Std Dev Precip Mar	-0.402	0.581	-0.69	0.489	-1.541	0.737
Std Dev Precip Apr	-0.619	0.567	-1.09	0.276	-1.731	0.494
Std Dev Precip May	1.573	0.462	3.40	0.001	0.666	2.480
Std Dev Precip Jun	-0.071	0.412	-0.17	0.862	-0.880	0.737
Std Dev Precip Jul	-0.329	0.372	-0.88	0.377	-1.058	0.401
Std Dev Precip Aug	-2.208	0.416	-5.31	0.000	-3.023	-1.392
Std Dev Precip Sep	1.455	0.376	3.87	0.000	0.719	2.192
Std Dev Precip Oct	-3.455	0.530	-6.52	0.000	-4.494	-2.416
Std Dev Precip Nov	0.567	0.467	1.21	0.225	-0.349	1.484
Std Dev Precip Dec	-1.868	0.496	-3.76	0.000	-2.841	-0.895
Std Dev Temp Jan	-1.670	0.489	-3.42	0.001	-2.628	-0.712
Std Dev Temp Feb	0.207	0.548	0.38	0.705	-0.867	1.281
Std Dev Temp Mar	1.556	0.517	3.01	0.003	0.542	2.571
Std Dev Temp Apr	-1.433	0.532	-2.69	0.007	-2.476	-0.389
Std Dev Temp May	-1.799	0.518	-3.47	0.001	-2.815	-0.783
Std Dev Temp Jun	-1.139	0.583	-1.95	0.051	-2.283	0.005
Std Dev Temp Jul	0.471	0.569	0.83	0.407	-0.644	1.587
Std Dev Temp Aug	0.355	0.590	0.60	0.548	-0.802	1.511
Std Dev Temp Sep	0.578	0.622	0.93	0.352	-0.641	1.798
Std Dev Temp Oct	2.327	0.638	3.65	0.000	1.076	3.579
Std Dev Temp Nov	-0.075	0.626	-0.12	0.905	-1.303	1.154
Std Dev Temp Dec	0.616	0.648	0.95	0.342	-0.656	1.887
Heartland	1.530	0.532	2.88	0.004	0.487	2.573
Northern Great Plains	-0.571	0.847	-0.67	0.500	-2.231	1.089
Prairie Gateway	1.045	0.843	1.24	0.215	-0.608	2.698
Eastern Uplands	-0.240	0.642	-0.37	0.709	-1.498	1.019
Southern Seaboard	-0.697	0.727	-0.96	0.338	-2.123	0.730
Fruitful Rim	-0.203	0.928	-0.22	0.827	-2.023	1.617
Basin And Range	-2.566	0.966	-2.66	0.008	-4.459	-0.672
Mississippi Portal	-2.440	0.847	-2.88	0.004	-4.100	-0.780
Constant	-10.907	5.366	-2.03	0.042	-21.431	-0.383

Tobit Estimation Results: Milk Cow Inventory, Census Data

($\chi^2_{(59)}$ = 1470; Pr>χ^2 = 0.000; *pseudo* R^2 = 0.12)

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
ln(Land Area)	1.428	0.096	14.91	0.000	1.240	1.616
ln(Water Area)	-0.221	0.040	-5.58	0.000	-0.299	-0.143
ln(Population)	0.420	0.046	9.21	0.000	0.330	0.509
Mean Precip Jan	-0.218	0.356	-0.61	0.541	-0.915	0.480
Mean Precip Feb	-0.300	0.434	-0.69	0.490	-1.152	0.552
Mean Precip Mar	0.265	0.365	0.73	0.467	-0.450	0.980
Mean Precip Apr	-0.354	0.341	-1.04	0.299	-1.022	0.314
Mean Precip May	-0.538	0.281	-1.92	0.055	-1.088	0.012
Mean Precip Jun	1.277	0.242	5.28	0.000	0.803	1.751
Mean Precip Jul	-1.415	0.218	-6.49	0.000	-1.842	-0.988
Mean Precip Aug	0.797	0.252	3.16	0.002	0.302	1.292
Mean Precip Sep	0.172	0.259	0.66	0.508	-0.337	0.680
Mean Precip Oct	-0.484	0.307	-1.58	0.115	-1.085	0.117
Mean Precip Nov	0.751	0.299	2.51	0.012	0.164	1.338
Mean Precip Dec	0.266	0.336	0.79	0.428	-0.392	0.925
Mean Temp Jan	-0.488	0.229	-2.12	0.034	-0.938	-0.038
Mean Temp Feb	0.590	0.209	2.82	0.005	0.179	1.000
Mean Temp Mar	-0.328	0.184	-1.78	0.075	-0.689	0.033

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
Mean Temp Apr	0.159	0.205	0.78	0.437	-0.242	0.560
Mean Temp May	-0.732	0.227	-3.22	0.001	-1.178	-0.287
Mean Temp Jun	0.821	0.204	4.03	0.000	0.422	1.221
Mean Temp Jul	-0.847	0.255	-3.32	0.001	-1.347	-0.346
Mean Temp Aug	0.386	0.243	1.59	0.112	-0.091	0.862
Mean Temp Sep	0.361	0.227	1.59	0.111	-0.084	0.805
Mean Temp Oct	-0.080	0.260	-0.31	0.758	-0.589	0.429
Mean Temp Nov	0.657	0.214	3.07	0.002	0.238	1.077
Mean Temp Dec	-0.585	0.255	-2.30	0.022	-1.086	-0.085
Std Dev Precip Jan	-0.290	0.304	-0.95	0.341	-0.887	0.307
Std Dev Precip Feb	0.932	0.386	2.42	0.016	0.175	1.689
Std Dev Precip Mar	0.773	0.303	2.55	0.011	0.178	1.368
Std Dev Precip Apr	-0.657	0.291	-2.26	0.024	-1.227	-0.087
Std Dev Precip May	0.145	0.245	0.59	0.555	-0.335	0.625
Std Dev Precip Jun	0.030	0.216	0.14	0.889	-0.393	0.454
Std Dev Precip Jul	-0.214	0.191	-1.12	0.262	-0.588	0.160
Std Dev Precip Aug	-0.712	0.214	-3.33	0.001	-1.132	-0.292
Std Dev Precip Sep	0.172	0.193	0.89	0.374	-0.207	0.551
Std Dev Precip Oct	-0.521	0.264	-1.97	0.049	-1.038	-0.003
Std Dev Precip Nov	-0.193	0.248	-0.78	0.437	-0.678	0.293
Std Dev Precip Dec	-0.736	0.261	-2.82	0.005	-1.248	-0.224
Std Dev Temp Jan	-0.387	0.252	-1.54	0.125	-0.882	0.107
Std Dev Temp Feb	-0.269	0.283	-0.95	0.341	-0.824	0.285
Std Dev Temp Mar	0.480	0.265	1.81	0.071	-0.040	1.000
Std Dev Temp Apr	-0.776	0.269	-2.89	0.004	-1.303	-0.249
Std Dev Temp May	-1.172	0.274	-4.27	0.000	-1.710	-0.634
Std Dev Temp Jun	0.515	0.305	1.69	0.091	-0.083	1.112
Std Dev Temp Jul	-0.003	0.286	-0.01	0.992	-0.564	0.558
Std Dev Temp Aug	-0.501	0.289	-1.73	0.083	-1.067	0.066
Std Dev Temp Sep	0.471	0.329	1.43	0.153	-0.175	1.116
Std Dev Temp Oct	0.276	0.336	0.82	0.412	-0.383	0.934
Std Dev Temp Nov	-0.030	0.324	-0.09	0.927	-0.665	0.606
Std Dev Temp Dec	0.675	0.337	2.00	0.045	0.014	1.337
Heartland	-0.712	0.302	-2.36	0.018	-1.303	-0.121
Northern Great Plains	-2.321	0.459	-5.06	0.000	-3.221	-1.421
Prairie Gateway	-0.919	0.445	-2.07	0.039	-1.791	-0.047
Eastern Uplands	-0.957	0.359	-2.67	0.008	-1.661	-0.253
Southern Seaboard	-0.851	0.397	-2.14	0.032	-1.629	-0.073
Fruitful Rim	-1.220	0.477	-2.56	0.011	-2.155	-0.284
Basin And Range	-3.179	0.493	-6.44	0.000	-4.147	-2.212
Mississippi Portal	-2.669	0.455	-5.87	0.000	-3.561	-1.777
Constant	-7.910	2.730	-2.90	0.004	-13.263	-2.557

Tobit Estimation Results: Beef Cattle Inventory, Survey Data

($\chi^2_{(59)}$ = 3146; Pr>χ^2 = 0.000; *pseudo* R^2 = 0.22)

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
ln(Land Area)	1.351	0.098	13.72	0.000	1.158	1.544
ln(Water Area)	-0.200	0.041	-4.91	0.000	-0.281	-0.120
ln(Population)	-0.027	0.047	-0.58	0.561	-0.120	0.065
Mean Precip Jan	-2.069	0.364	-5.68	0.000	-2.783	-1.355
Mean Precip Feb	0.981	0.446	2.20	0.028	0.106	1.856
Mean Precip Mar	-1.316	0.377	-3.49	0.000	-2.056	-0.576
Mean Precip Apr	-1.015	0.347	-2.92	0.003	-1.695	-0.334
Mean Precip May	0.393	0.288	1.36	0.173	-0.173	0.958
Mean Precip Jun	1.135	0.247	4.60	0.000	0.652	1.619
Mean Precip Jul	-0.857	0.222	-3.86	0.000	-1.292	-0.422
Mean Precip Aug	0.240	0.256	0.93	0.350	-0.263	0.742
Mean Precip Sep	-0.080	0.267	-0.30	0.763	-0.604	0.443
Mean Precip Oct	0.739	0.320	2.31	0.021	0.112	1.367
Mean Precip Nov	0.477	0.319	1.49	0.136	-0.150	1.103
Mean Precip Dec	2.211	0.349	6.33	0.000	1.526	2.896
Mean Temp Jan	-0.775	0.231	-3.36	0.001	-1.227	-0.323
Mean Temp Feb	-0.370	0.219	-1.69	0.092	-0.800	0.060
Mean Temp Mar	0.794	0.190	4.18	0.000	0.421	1.166
Mean Temp Apr	-0.961	0.212	-4.53	0.000	-1.377	-0.545
Mean Temp May	0.281	0.232	1.21	0.227	-0.175	0.736
Mean Temp Jun	0.179	0.208	0.86	0.392	-0.230	0.587
Mean Temp Jul	-0.158	0.262	-0.60	0.547	-0.672	0.356
Mean Temp Aug	-0.106	0.247	-0.43	0.668	-0.591	0.379
Mean Temp Sep	-1.381	0.227	-6.09	0.000	-1.826	-0.936
Mean Temp Oct	2.307	0.260	8.88	0.000	1.798	2.817
Mean Temp Nov	-0.545	0.215	-2.53	0.011	-0.967	-0.123
Mean Temp Dec	0.725	0.259	2.80	0.005	0.218	1.232
Std Dev Precip Jan	-0.147	0.311	-0.47	0.636	-0.756	0.462
Std Dev Precip Feb	1.124	0.401	2.80	0.005	0.337	1.911
Std Dev Precip Mar	1.560	0.310	5.02	0.000	0.951	2.169
Std Dev Precip Apr	1.097	0.291	3.77	0.000	0.526	1.668
Std Dev Precip May	0.094	0.250	0.38	0.707	-0.396	0.583
Std Dev Precip Jun	-0.301	0.227	-1.32	0.186	-0.747	0.145
Std Dev Precip Jul	0.120	0.194	0.62	0.536	-0.261	0.501
Std Dev Precip Aug	-1.501	0.219	-6.85	0.000	-1.931	-1.071
Std Dev Precip Sep	0.863	0.201	4.29	0.000	0.468	1.258
Std Dev Precip Oct	-0.270	0.271	-1.00	0.318	-0.802	0.261
Std Dev Precip Nov	-2.772	0.265	-10.44	0.000	-3.292	-2.251
Std Dev Precip Dec	-0.804	0.268	-3.00	0.003	-1.329	-0.278
Std Dev Temp Jan	-0.248	0.261	-0.95	0.343	-0.761	0.265
Std Dev Temp Feb	-0.065	0.290	-0.23	0.822	-0.634	0.503
Std Dev Temp Mar	-0.229	0.272	-0.84	0.401	-0.763	0.305
Std Dev Temp Apr	1.112	0.273	4.07	0.000	0.577	1.647
Std Dev Temp May	-2.968	0.281	-10.57	0.000	-3.518	-2.417
Std Dev Temp Jun	2.292	0.314	7.30	0.000	1.676	2.907
Std Dev Temp Jul	1.157	0.294	3.94	0.000	0.581	1.733
Std Dev Temp Aug	-0.146	0.288	-0.51	0.613	-0.712	0.420
Std Dev Temp Sep	0.276	0.344	0.80	0.423	-0.399	0.950
Std Dev Temp Oct	-0.151	0.345	-0.44	0.661	-0.828	0.526
Std Dev Temp Nov	1.073	0.330	3.25	0.001	0.426	1.720
Std Dev Temp Dec	-0.173	0.343	-0.51	0.613	-0.845	0.498
Heartland	6.060	0.350	17.33	0.000	5.375	6.746
Northern Great Plains	4.625	0.482	9.60	0.000	3.681	5.570

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
Prairie Gateway	4.729	0.479	9.87	0.000	3.790	5.669
Eastern Uplands	5.122	0.414	12.36	0.000	4.310	5.935
Southern Seaboard	5.622	0.443	12.68	0.000	4.753	6.491
Fruitful Rim	3.949	0.497	7.95	0.000	2.975	4.922
Basin And Range	4.589	0.518	8.87	0.000	3.574	5.604
Mississippi Portal	3.447	0.478	7.22	0.000	2.511	4.384
Constant	-5.861	2.799	-2.09	0.036	-11.350	-0.372

Tobit Estimation Results: Beef Cattle Inventory, Census Data

($\chi^2_{(59)}$ = 2574; Pr>χ^2 = 0.000; *pseudo* R^2 = 0.24)

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
ln(Land Area)	1.773	0.042	42.02	0.000	1.690	1.855
ln(Water Area)	-0.102	0.018	-5.61	0.000	-0.138	-0.066
ln(Population)	-0.084	0.021	-4.04	0.000	-0.126	-0.043
Mean Precip Jan	-0.205	0.164	-1.24	0.213	-0.527	0.118
Mean Precip Feb	-0.102	0.201	-0.51	0.612	-0.496	0.292
Mean Precip Mar	0.162	0.167	0.97	0.334	-0.167	0.490
Mean Precip Apr	-0.471	0.156	-3.02	0.003	-0.777	-0.166
Mean Precip May	0.149	0.130	1.15	0.251	-0.106	0.403
Mean Precip Jun	0.802	0.111	7.20	0.000	0.583	1.020
Mean Precip Jul	-0.779	0.100	-7.76	0.000	-0.976	-0.582
Mean Precip Aug	0.085	0.116	0.73	0.463	-0.143	0.314
Mean Precip Sep	0.098	0.119	0.82	0.412	-0.136	0.332
Mean Precip Oct	-0.264	0.141	-1.87	0.061	-0.540	0.012
Mean Precip Nov	0.137	0.138	0.99	0.323	-0.135	0.408
Mean Precip Dec	0.315	0.155	2.03	0.042	0.011	0.619
Mean Temp Jan	-0.082	0.106	-0.77	0.439	-0.291	0.126
Mean Temp Feb	-0.102	0.097	-1.05	0.292	-0.293	0.088
Mean Temp Mar	-0.008	0.085	-0.09	0.928	-0.175	0.160
Mean Temp Apr	0.326	0.095	3.44	0.001	0.140	0.512
Mean Temp May	-0.585	0.105	-5.57	0.000	-0.790	-0.379
Mean Temp Jun	0.265	0.094	2.81	0.005	0.080	0.450
Mean Temp Jul	-0.125	0.118	-1.06	0.290	-0.356	0.107
Mean Temp Aug	-0.297	0.113	-2.63	0.009	-0.518	-0.076
Mean Temp Sep	0.521	0.104	5.00	0.000	0.317	0.725
Mean Temp Oct	0.071	0.120	0.59	0.554	-0.164	0.305
Mean Temp Nov	0.193	0.099	1.95	0.051	-0.001	0.387
Mean Temp Dec	-0.168	0.118	-1.42	0.156	-0.399	0.064
Std Dev Precip Jan	-0.320	0.140	-2.28	0.023	-0.596	-0.045
Std Dev Precip Feb	0.479	0.178	2.68	0.007	0.129	0.828
Std Dev Precip Mar	0.277	0.139	1.99	0.047	0.004	0.550
Std Dev Precip Apr	-0.050	0.132	-0.38	0.705	-0.309	0.209
Std Dev Precip May	0.168	0.113	1.49	0.136	-0.053	0.388
Std Dev Precip Jun	0.112	0.100	1.12	0.264	-0.084	0.307
Std Dev Precip Jul	0.052	0.088	0.59	0.555	-0.120	0.223
Std Dev Precip Aug	-0.353	0.099	-3.58	0.000	-0.546	-0.159
Std Dev Precip Sep	0.218	0.089	2.45	0.015	0.043	0.392
Std Dev Precip Oct	-0.222	0.122	-1.82	0.068	-0.461	0.017
Std Dev Precip Nov	-0.176	0.115	-1.53	0.125	-0.401	0.049
Std Dev Precip Dec	-0.348	0.119	-2.92	0.004	-0.582	-0.114
Std Dev Temp Jan	0.116	0.116	1.00	0.319	-0.112	0.344

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
Std Dev Temp Feb	-0.642	0.131	-4.90	0.000	-0.899	-0.385
Std Dev Temp Mar	0.234	0.123	1.91	0.056	-0.006	0.475
Std Dev Temp Apr	-0.355	0.124	-2.86	0.004	-0.599	-0.111
Std Dev Temp May	-0.720	0.126	-5.70	0.000	-0.968	-0.473
Std Dev Temp Jun	0.632	0.141	4.48	0.000	0.355	0.908
Std Dev Temp Jul	0.080	0.132	0.61	0.544	-0.179	0.339
Std Dev Temp Aug	-0.088	0.134	-0.66	0.510	-0.351	0.174
Std Dev Temp Sep	0.269	0.153	1.76	0.079	-0.031	0.569
Std Dev Temp Oct	-0.318	0.155	-2.05	0.041	-0.622	-0.014
Std Dev Temp Nov	0.360	0.150	2.40	0.017	0.065	0.654
Std Dev Temp Dec	0.280	0.155	1.80	0.072	-0.025	0.585
Heartland	-0.468	0.140	-3.33	0.001	-0.743	-0.193
Northern Great Plains	-0.978	0.214	-4.56	0.000	-1.399	-0.558
Prairie Gateway	-0.572	0.207	-2.77	0.006	-0.978	-0.167
Eastern Uplands	0.004	0.167	0.03	0.979	-0.323	0.332
Southern Seaboard	-0.290	0.184	-1.58	0.114	-0.651	0.070
Fruitful Rim	-0.466	0.220	-2.12	0.034	-0.897	-0.035
Basin And Range	-1.230	0.229	-5.38	0.000	-1.679	-0.782
Mississippi Portal	-0.744	0.207	-3.60	0.000	-1.149	-0.338
Constant	-3.634	1.259	-2.89	0.004	-6.103	-1.165

Tobit Estimation Results: Hogs and Pigs Inventory, Census Data

($\chi^2_{(59)}$ = 2655; Pr>χ^2 = 0.000; *pseudo* R^2 = 0.19)

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
ln(Land Area)	1.705	0.067	25.45	0.000	1.574	1.836
ln(Water Area)	-0.196	0.028	-7.10	0.000	-0.250	-0.142
ln(Population)	0.160	0.032	5.02	0.000	0.097	0.222
Mean Precip Jan	0.692	0.242	2.86	0.004	0.218	1.167
Mean Precip Feb	-0.637	0.300	-2.12	0.034	-1.226	-0.048
Mean Precip Mar	0.383	0.250	1.53	0.125	-0.107	0.874
Mean Precip Apr	0.012	0.234	0.05	0.958	-0.447	0.471
Mean Precip May	0.353	0.191	1.85	0.064	-0.021	0.727
Mean Precip Jun	0.684	0.165	4.14	0.000	0.360	1.008
Mean Precip Jul	-1.252	0.148	-8.48	0.000	-1.542	-0.962
Mean Precip Aug	0.261	0.174	1.51	0.132	-0.079	0.602
Mean Precip Sep	0.524	0.176	2.97	0.003	0.178	0.869
Mean Precip Oct	-0.376	0.208	-1.80	0.071	-0.784	0.033
Mean Precip Nov	-0.457	0.210	-2.17	0.030	-0.869	-0.044
Mean Precip Dec	-0.054	0.236	-0.23	0.817	-0.516	0.408
Mean Temp Jan	-0.328	0.159	-2.06	0.040	-0.640	-0.015
Mean Temp Feb	-0.484	0.148	-3.27	0.001	-0.774	-0.194
Mean Temp Mar	0.041	0.129	0.32	0.751	-0.211	0.293
Mean Temp Apr	0.804	0.142	5.64	0.000	0.525	1.084
Mean Temp May	-0.660	0.158	-4.17	0.000	-0.970	-0.350
Mean Temp Jun	-0.157	0.142	-1.11	0.269	-0.436	0.122
Mean Temp Jul	0.611	0.179	3.42	0.001	0.261	0.961
Mean Temp Aug	-1.329	0.171	-7.75	0.000	-1.665	-0.993
Mean Temp Sep	1.517	0.158	9.61	0.000	1.207	1.826
Mean Temp Oct	-0.528	0.180	-2.93	0.003	-0.881	-0.175
Mean Temp Nov	0.331	0.145	2.27	0.023	0.046	0.616
Mean Temp Dec	0.188	0.176	1.07	0.286	-0.157	0.534

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
Std Dev Precip Jan	0.513	0.207	2.47	0.013	0.106	0.919
Std Dev Precip Feb	-0.013	0.269	-0.05	0.962	-0.539	0.514
Std Dev Precip Mar	-0.233	0.210	-1.11	0.269	-0.645	0.180
Std Dev Precip Apr	-0.819	0.198	-4.14	0.000	-1.208	-0.431
Std Dev Precip May	-0.381	0.170	-2.24	0.025	-0.716	-0.047
Std Dev Precip Jun	-0.233	0.151	-1.54	0.125	-0.530	0.064
Std Dev Precip Jul	0.259	0.131	1.98	0.047	0.003	0.516
Std Dev Precip Aug	0.126	0.146	0.86	0.389	-0.160	0.412
Std Dev Precip Sep	0.542	0.133	4.07	0.000	0.281	0.804
Std Dev Precip Oct	-0.275	0.179	-1.54	0.124	-0.627	0.076
Std Dev Precip Nov	0.148	0.174	0.85	0.393	-0.192	0.489
Std Dev Precip Dec	0.303	0.182	1.66	0.097	-0.054	0.660
Std Dev Temp Jan	-0.310	0.178	-1.75	0.081	-0.659	0.038
Std Dev Temp Feb	0.036	0.198	0.18	0.854	-0.352	0.424
Std Dev Temp Mar	0.176	0.186	0.95	0.344	-0.189	0.540
Std Dev Temp Apr	-0.425	0.187	-2.27	0.023	-0.792	-0.057
Std Dev Temp May	-0.970	0.192	-5.06	0.000	-1.346	-0.594
Std Dev Temp Jun	0.391	0.213	1.84	0.066	-0.026	0.808
Std Dev Temp Jul	-0.123	0.199	-0.62	0.536	-0.513	0.267
Std Dev Temp Aug	0.140	0.197	0.71	0.478	-0.247	0.526
Std Dev Temp Sep	0.628	0.230	2.73	0.006	0.176	1.079
Std Dev Temp Oct	-0.981	0.237	-4.13	0.000	-1.447	-0.515
Std Dev Temp Nov	0.896	0.225	3.98	0.000	0.454	1.338
Std Dev Temp Dec	-0.242	0.233	-1.04	0.299	-0.699	0.215
Heartland	1.573	0.217	7.24	0.000	1.147	1.999
Northern Great Plains	-0.931	0.332	-2.81	0.005	-1.582	-0.281
Prairie Gateway	-0.191	0.312	-0.61	0.542	-0.803	0.422
Eastern Uplands	-0.858	0.258	-3.32	0.001	-1.365	-0.352
Southern Seaboard	-0.514	0.281	-1.83	0.068	-1.066	0.038
Fruitful Rim	-0.878	0.330	-2.66	0.008	-1.525	-0.232
Basin And Range	-0.766	0.347	-2.21	0.027	-1.445	-0.086
Mississippi Portal	-0.985	0.314	-3.14	0.002	-1.601	-0.370
Constant	-10.379	1.910	-5.43	0.000	-14.125	-6.634

Tobit Estimation Results: Poultry Inventory, Census Data

($\chi^2_{(59)}$ = 1361; Pr>χ^2 = 0.000; *pseudo R^2* = 0.11)

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
ln(Land Area)	1.995	0.093	21.41	0.000	1.812	2.177
ln(Water Area)	-0.179	0.041	-4.37	0.000	-0.259	-0.099
ln(Population)	0.171	0.047	3.64	0.000	0.079	0.264
Mean Precip Jan	0.844	0.348	2.43	0.015	0.162	1.527
Mean Precip Feb	0.530	0.438	1.21	0.226	-0.328	1.388
Mean Precip Mar	0.034	0.362	0.09	0.924	-0.675	0.744
Mean Precip Apr	0.969	0.342	2.83	0.005	0.299	1.639
Mean Precip May	0.416	0.279	1.49	0.136	-0.131	0.964
Mean Precip Jun	0.617	0.237	2.61	0.009	0.153	1.081
Mean Precip Jul	-1.121	0.221	-5.07	0.000	-1.555	-0.687
Mean Precip Aug	0.332	0.255	1.30	0.193	-0.168	0.831
Mean Precip Sep	0.656	0.256	2.56	0.011	0.154	1.157
Mean Precip Oct	-0.194	0.299	-0.65	0.516	-0.780	0.392
Mean Precip Nov	-0.490	0.302	-1.63	0.104	-1.082	0.101
Mean Precip Dec	-0.799	0.338	-2.36	0.018	-1.463	-0.135
Mean Temp Jan	-0.788	0.234	-3.37	0.001	-1.246	-0.329
Mean Temp Feb	0.073	0.217	0.34	0.735	-0.352	0.499
Mean Temp Mar	-0.081	0.190	-0.43	0.670	-0.453	0.292
Mean Temp Apr	0.797	0.208	3.84	0.000	0.390	1.205
Mean Temp May	-1.303	0.231	-5.64	0.000	-1.756	-0.849
Mean Temp Jun	0.959	0.209	4.58	0.000	0.548	1.369
Mean Temp Jul	-0.553	0.262	-2.11	0.035	-1.068	-0.039
Mean Temp Aug	-0.071	0.254	-0.28	0.779	-0.569	0.427
Mean Temp Sep	0.729	0.236	3.08	0.002	0.265	1.192
Mean Temp Oct	0.177	0.273	0.65	0.518	-0.359	0.713
Mean Temp Nov	-0.759	0.219	-3.46	0.001	-1.190	-0.329
Mean Temp Dec	0.903	0.263	3.44	0.001	0.388	1.418
Std Dev Precip Jan	0.095	0.303	0.31	0.754	-0.499	0.689
Std Dev Precip Feb	1.148	0.387	2.96	0.003	0.388	1.907
Std Dev Precip Mar	-0.233	0.303	-0.77	0.443	-0.827	0.362
Std Dev Precip Apr	-0.746	0.290	-2.58	0.010	-1.314	-0.178
Std Dev Precip May	-1.734	0.248	-7.00	0.000	-2.219	-1.248
Std Dev Precip Jun	-0.353	0.218	-1.62	0.105	-0.779	0.074
Std Dev Precip Jul	0.570	0.194	2.94	0.003	0.190	0.950
Std Dev Precip Aug	0.039	0.218	0.18	0.858	-0.389	0.466
Std Dev Precip Sep	-0.256	0.193	-1.33	0.185	-0.634	0.123
Std Dev Precip Oct	-0.244	0.259	-0.94	0.346	-0.752	0.264
Std Dev Precip Nov	-0.461	0.252	-1.83	0.067	-0.955	0.033
Std Dev Precip Dec	0.129	0.263	0.49	0.625	-0.387	0.644
Std Dev Temp Jan	-0.068	0.264	-0.26	0.797	-0.585	0.449
Std Dev Temp Feb	-0.715	0.293	-2.44	0.015	-1.289	-0.141
Std Dev Temp Mar	-0.029	0.273	-0.11	0.914	-0.564	0.505
Std Dev Temp Apr	-0.974	0.279	-3.49	0.000	-1.522	-0.427
Std Dev Temp May	-0.833	0.287	-2.91	0.004	-1.395	-0.271
Std Dev Temp Jun	0.713	0.313	2.28	0.023	0.100	1.327
Std Dev Temp Jul	0.389	0.297	1.31	0.191	-0.194	0.971
Std Dev Temp Aug	1.194	0.292	4.09	0.000	0.622	1.765
Std Dev Temp Sep	-0.194	0.339	-0.57	0.568	-0.859	0.471
Std Dev Temp Oct	-1.119	0.346	-3.23	0.001	-1.797	-0.440
Std Dev Temp Nov	0.337	0.334	1.01	0.313	-0.318	0.991
Std Dev Temp Dec	0.055	0.349	0.16	0.874	-0.629	0.740
Heartland	-1.453	0.315	-4.61	0.000	-2.071	-0.835
Northern Great Plains	-2.496	0.502	-4.98	0.000	-3.480	-1.513

Variable	Estimated Coefficient	Standard Error	t-Ratio	Pr>|t|	95% Confidence Interval	
Prairie Gateway	-2.882	0.450	-6.41	0.000	-3.763	-2.000
Eastern Uplands	-1.289	0.368	-3.50	0.000	-2.011	-0.566
Southern Seaboard	-0.643	0.406	-1.58	0.114	-1.440	0.154
Fruitful Rim	-2.961	0.477	-6.20	0.000	-3.898	-2.025
Basin And Range	-3.600	0.508	-7.09	0.000	-4.595	-2.604
Mississippi Portal	-4.127	0.453	-9.11	0.000	-5.016	-3.238
Constant	-13.566	2.804	-4.84	0.000	-19.065	-8.067

A.4. Projections

To make projections of changes in livestock inventories, we first computed county-level, monthly changes in mean temperature (in °F) and precipitation (in inches) between a reference period (1971-2000) and a mid-century period (2041-2070) based on the statistically downscaled climate projections in the *2015 Pennsylvania Climate Impacts Assessment Update* (Shortle et al., 2015). Taking the midpoints of the two periods (1985 and 2055), these projected changes cover a period of 70 years. On the other hand, taking the difference between 2050 and the midpoint of our livestock inventory data (2013 for the survey data and 2012 for the Census data) yields a figure of 37 or 38 years. We adjusted the projected temperature and precipitation changes to a 38-year period assuming that the changes are linear, i.e. the change over 38 years is $38/70 \approx 0.54$ of the change over 70 years.

For precipitation, we assumed that the standard deviation for each month would change by the same percentage as that month's mean precipitation, so that the coefficient of variation in precipitation for each month does not change. For temperature, we assumed that the monthly standard deviations would not change. These represent fairly conservative assumptions about climate variability, which seems appropriate given uncertainty about how climate change might impact climate variability in Pennsylvania.

We then computed percentage changes in the projected values of livestock inventories using the changes between our base period (2012/2013) and 2050 in temperature and precipitation means and standard deviations. Land area, water area, and population were held constant, so that the projected changes in livestock inventories are those solely due to changes in the climate variables.

For milk cows and beef cattle, there are two projections each, one based on survey data and one based on Census data. We used an average of the percentage changes in inventory in the two projections. For hogs and pigs and for poultry, there is one projection each, based on Census data.

As national and global livestock markets adjust to changes in production caused by climate change, commodity prices facing Pennsylvania livestock producers could change, leading to changes in livestock inventories that the regression models cannot account for since they implicitly assume that prices do not change (Cline, 1996). We address this limitation by incorporating into our projections an expansion in Pennsylvania's livestock sector in response to higher livestock prices due to climate change.

The IPCC Fifth Assessment Report on food security and food production systems (Porter et al., 2014) finds that it is very likely that changes in temperature and precipitation, without considering CO_2 fertilization effects, will lead to increased global food prices by 2050. For the projections here we assume a 10% increase in livestock product prices relative to feed prices, so that there is an incentive to increase livestock herds. Increases in livestock inventories in Pennsylvania counties due to this relative price increase are based on supply elasticities in Revell (2015) of approximately 0.8 for milk, 0.4 for beef, 0.7 for pigs, and 0.6 for poultry. These increases in inventories are added to the changes in inventories based on the regression model results to yield the changes in inventories presented in Section 6 of this report.

As noted above, we used the projected changes in livestock inventories to make projections of changes in nitrogen and phosphorus generated per day by livestock production. These nutrient projections rely on estimates for common livestock species from the American Society of Agricultural Engineers (ASAE) (2005) of nutrient production per animal per day. For milk cows, we used a weighted average of figures per day-animal for lactating cows (75% weight) and dry cows (25% weight), with the weights based on figures for Pennsylvania in Weeks (2016). For beef cattle, we used figures for finishing cattle. For hogs and pigs, we used figures for grow-finish swine, and for poultry we used figures for chicken broilers. The figures for finishing cattle, grow-finish swine, and broilers are totals per animal, which were converted to totals per day-animal by dividing by the finishing time period for each animal assumed by ASAE.

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Chapter 2 Climate Change Impacts on Pennsylvania's Watershed Management Strategies and Water Quality Goals[1]

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1. Introduction

Pennsylvania is required by the Chesapeake Bay Total Maximum Daily Load (TMDL) to meet specific nutrient pollution load reductions requirements by 2025. The practices and methods the state seeks to achieve these requirements are set forth in "Final Phase 3 Watershed Implementation Plan" (Phase 3 WIP). Underlying the Phase 3 WIP is an understanding of the relationships between land uses and pollution control practices embodied in the US EPA Chesapeake Bay Watershed Model (CBWM).

Assessments of the effectiveness of the Phase 3 WIP have been made using the CBWM based on climate data from the 20th century. Expected climate change will, however, impact drivers of water quality throughout the Bay watershed. CBWM simulations that examine the impacts of climate change across the Bay watershed indicate that nutrient loads will increase without appropriate adaptations. Accordingly, local and countywide planning associated with the Phase 3 WIP should also consider these changing conditions.

This work will focus on recent research in Pennsylvania and the Mid-Atlantic Region and include a review of recent literature to better understand the potential impacts of climate change on the effectiveness of current Best Management Practices (BMPs) specific to the landscapes and land use patterns of Pennsylvania. Based on reviews of pertinent literature, recent and ongoing research conducted by team members, and data and modeling analyses conducted for this project, this study aims to answer the following questions and provide recommendations for management actions and research needs to better inform Pennsylvania on decisions related to meeting water quality goals under a changing climate.

1. What impact will a changing climate have on the proposed tiered approach in the Phase 3 WIP for local and countywide goals?

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*[1] This report is a deliverable for a Penn State contract with the Pennsylvania Department of Environmental Protection (DEP), PA 2018 Climate Change Impact Assessment. The authors would also like to thank DEP staff for their consultations during the work on this report

2. What potential impact will projected 21st century climate change have on the suitability and effectiveness of water quality driven BMPs (e.g., forested riparian buffers and cover crops) across the different landscapes and ecoregions of Pennsylvania?

3. What new recommendations or changes to current management practices (e.g., buffer site selection, frequency of invasive vegetation control efforts, etc.) might Pennsylvania adopt in order to increase the effectiveness of BMPs in Pennsylvania as the climate continues to change?

2. Key Findings and Conclusions

1. Expected climate change will increase the primary weather drivers of nonpoint pollution (rainfall and runoff events). Increases in the annual average volumes of runoff from agricultural and urban lands that must be treated to meet TMDL goals are expected.
2. Climate change will increase the variability of runoff events, including changes to extremes that may be more significant to water quality outcomes than changes to annual averages. Adjustments to BMP selection and location, as well as changes to modeling and policy may be needed to mitigate the effects of changes in extremes.
3. Spatial variations in climate change across the state and responses to climate change may result in changes in the spatial distribution of resources and new prioritizations of critical watersheds.
4. While expected climate change will increase the need for treatment of runoff, it may also decrease the effectiveness of some BMPs. Management adaptations to address the overall increase in runoff that requires treatment and the reduction in the efficiency of some climate-vulnerable BMPs will be required.
5. Climate change will necessitate changes in how BMPs are evaluated (evaluation criteria). In particular, analysis of the resilience to emerging weather risks is needed.
6. Structural BMPs are especially vulnerable to climate change. Appropriate adaptations will vary by practice but should generally include design standards and criteria for placement for optimal performance. Greater attention to monitoring and maintenance will be needed to assure continued design performance.
7. The performance of non-structural BMPs is generally less vulnerable to expected climate change but optimal implementation will require new guidance (e.g., N and P uptake, realistic target yields, etc. for nutrient planning).
8. Given scarce resources for BMP implementation, maintenance, monitoring, and enforcement, the importance of following fundamental principles of cost- effective water quality protection will be crucial to coping efficiently and effectively with challenges posed by expected climate change. For the sake of effectiveness and efficiency, smart choices of BMP types and their spatial placement is crucial. The impact of resources devoted to Nonpoint Source (NPS) control depends critically on the specific BMPs implemented, the location of the BMPs, and the maintenance of the BMPs. Context-sensitive design (i.e., not one size fits all) is essential for cost-effective structural BMPs. Design choices must also be realistic and

consider effects of climate change, as well as pragmatic versus ideal maintenance practices (e.g. trees versus grasses).

9. Climate change will increase the local benefits of BMPs that promote soil health etc. by enhancing the agronomic and economic resilience of agricultural production.
10. How much more PA must do to address climate change impacts on pollution loads will depend on a variety of factors. These include the changes in the drivers, climate driven changes (adaptations) in land use and land cover, and the effects of climate change on the functionality (efficiency, resilience) of BMPs.

3. PA Watershed Implementation Plans for the Chesapeake Bay and Climate Change

Given the objectives of this report, we begin with a review of the Chesapeake Bay TMDL, Pennsylvania's Phase 3 WIP and DEP's tiered approach to implementation, and prior EPA analysis of the implications of climate for nutrient loads. This section also presents a categorization of BMPs included in the Phase 3 WIP that is useful for analysis of vulnerability and resilience to climate change.

3.1 The Chesapeake Bay TMDL

In December 2010, as required by the federal Clean Water Act, the U.S. Environmental Protection Agency (EPA) finalized the Chesapeake Bay Total Maximum Daily Load (TMDL). The TMDL establishes allowable loads for nitrogen, phosphorus and sediment sufficient to meet water quality standards for the Chesapeake Bay, and the necessary load reductions that must be made to achieve water quality goals. It requires states within the Bay watershed to develop and implement watershed implementation plans (WIPs) in three phases to meet their responsible load reductions from all sectors.

Pennsylvania developed its Phase 1 WIP in 2011 and it's Phase 2 WIP in 2012. A variety of nutrient and sediment reduction practices and strategies have been implemented since then to achieve reductions in loads in the wastewater treatment, agricultural and stormwater sectors.

In 2017-18, EPA's Chesapeake Bay Program (CBP), the regional partnership that oversees the Chesapeake Bay restoration effort, conducted a midpoint assessment of progress toward meeting TMDL goals. This midpoint assessment brought the best available data, science and modeling to assess progress and establish planning targets for meeting the TMDL by 2025. The midpoint assessment found that the Bay jurisdictions were on target to meet phosphorus and sediment goals but behind for nitrogen.

For Pennsylvania, nutrient planning targets to meet the TMDL require reductions of 51.06 million pounds/year of nitrogen and 2.02 million lbs/yr of phosphorus to local waterways (known as “edge of stream” reductions). These “edge of stream” reductions equate to 34.13 million lbs/yr of nitrogen and 0.756 million lbs/yr of phosphorus delivered to the Chesapeake Bay (known as “edge of tide” reductions).

3.2 The Phase 3 Watershed Implementation Plan (Phase 3 WIP)

From 2017-19, Pennsylvania and the other Bay jurisdictions developed their Phase 3 WIPs. This phase of Pennsylvania’s WIP development was unprecedented in the level of public participation and involvement in developing strategies and actions for meeting the planning targets. In addition, as distinguished from the Phase 1 and 2 WIPs, the Phase 3 WIP defined with much more specificity local targets and actions to accelerate implementation of measures at a very local level. Efforts were also made to prioritize areas with the highest reduction potential. The overall state planning targets were divided by county, and counties were prioritized in a four-tier approach by their load reduction opportunities.

Tier 1 represents those counties where load reduction efforts will allow the Commonwealth to meet 25% of its overall goal, and consist of Lancaster and York Counties, the southern-most counties along the Susquehanna River before it enters Maryland and flows to the Chesapeake Bay. Tier 2 counties provide the second 25% of reductions and get Pennsylvania halfway to its nutrient reduction goal. These include five additional counties, primarily in the southcentral (Franklin, Lebanon, Cumberland, Centre and Bedford Counties). Tier 3 provides the third 25% of reductions and consists of 16 counties. Finally, Tier 4, which represents the last 25% of reductions and allows Pennsylvania to meet its overall nutrient reduction goals, consists of 20 counties primarily in the northern and western parts of the watershed, several of which only partially contribute to the Chesapeake Bay drainage.

The Phase 3 WIP anticipates each of these 43 counties to develop “County Action Plans” (CAPs), specific initiatives and measures for implementation to achieve the nutrient reductions set forth in county planning targets. For four pilot counties, Lancaster and York (Tier 1), Franklin (Tier 2) and Adams (Tier 3), DEP and partners facilitated local stakeholder involvement in the CAP planning process as part of the Phase 3 WIP development. The final Phase 3 WIP includes the CAPs for these four pilot counties and describes actions that will be taken to develop similar plans for the other 39 counties in the Chesapeake Bay watershed.

The Phase 3 WIP also sets forth state-level goals, recommendations, and actions to be implemented across the watershed. These include priority practices and initiatives to provide nutrient reductions from specific sectors, including agriculture, urban stormwater, forestry, and wastewater.

Implementation of all nutrient reduction priority practices and initiatives set forth in the Phase 3 WIP is expected to achieve 73% of the nitrogen reduction planning target for Pennsylvania and exceed the phosphorus reduction planning target.

3.3 The Phase 3 WIP and Climate Change

As expressed in EPA's expectations for the Phase 3 WIP, Section 9 of Pennsylvania's Phase 3 WIP considers climate change impacts related to the Phase 3 WIP.

In this section, preliminary modeling results from the Chesapeake Bay Program Partnership are summarized which indicate that climate change impacts may require additional nutrient reductions to meet water quality goals for the Chesapeake Bay. For example, Pennsylvania's estimated reduction targets would increase by 4.135 million lbs/yr for nitrogen and 0.141 lbs/yr for phosphorus. To address these challenges related to climate change, the CBP Partnership committed to sharpening the science related to the impacts of climate change on meeting Chesapeake Bay water quality goals over the next two years and, in March 2021, consider the results of further scientific study and refine estimated loads due to climate change for each jurisdiction.

For the Phase 3 WIP, a narrative strategy was developed, which sets forth the Commonwealth's programmatic commitments to reduce greenhouse gas emissions contributing to climate change. In addition, the WIP acknowledges the PA Climate Change Act of 2008's mandate for DEP to study the potential impacts of global climate change on Pennsylvania, and the development of this report to explore the impacts of climate change on the livestock industry, the resiliency of critical infrastructure in the Commonwealth, and water quality, specifically the implications for meeting Pennsylvania's obligations under the Chesapeake Bay TMDL. This report helps fulfill this commitment set forth in the Phase 3 WIP, as mandated by the PA Climate Change Act of 2008.

3.4 Categories of Practices Analyzed in this Report

The focus of this study is on how climate change will impact land-based practices (best management practices, or BMPs) designed to reduce nutrient pollution to water from the landscape. Accordingly, we focus this report on those Phase 3 WIP recommendations for sectors related to land-based management processes for controlling nutrients (i.e., nonpoint sources of pollution from the agriculture and urban sectors). Because the specific BMPs related to the Phase 3 WIP priority recommendations for the sectors are varied and voluminous, for purposes of our analysis we organized suites of practices based on four landscape types found in agricultural/urban influenced landscapes: crops, livestock, stream/riparian, and urban. Several suites of practices are categorized in each of these four landscape types. These practice categories are listed in Table 1, along with the Phase 3 WIP priority initiative to which each category relates and an explanatory note.

Table 1. Categories of Phase 3 WIP-recommended practices analyzed in this report

Practice Category	Related Phase 3 WIP Priority Initiative	Notes
CROPS		
Terraces, Diversions and Grassed Waterways	Agricultural Compliance	These are structural practices to reduce erosion and sedimentation from crop fields which result in nutrient and sediment reductions to waters. They are practices that may be part of a farmer's agricultural erosion and sediment control plan or conservation plan, required as part of agricultural compliance in Pennsylvania.
Conservation Crop Rotations, Strip Cropping, and Contour Farming	Agricultural Compliance	These are management and operational-based practices whereby crop selection, rotation, and field layout and boundaries are carefully planned and executed to maximize production while minimizing soil and nutrient

		losses. They are practices that may be part of a farmer's agricultural erosion and sediment control plan or conservation plan, required as part of agricultural compliance in Pennsylvania.
No Till	Soil Health	No till and minimum tillage reduces soil and nutrient loss and is part of a holistic crop management program to improve soil health.
Cover Crops	Soil Health	Cover crops reduce soil and nutrient loss, can reduce necessary nutrient applications, and are part of a holistic crop management program to improve soil health.
Nutrient Management	Agricultural Compliance Expanded Nutrient Management	Core nutrient management of manure application on crop fields is required as part of agricultural compliance in Pennsylvania. Expanded nutrient management (including nutrient management for crops not receiving manure and application of the 4Rs of nutrient management) provides additional nutrient reductions by more precisely tailoring nutrient applications to crop needs.

LIVESTOCK		
Pasture Management	Soil Health	Prescribed grazing of livestock to manage pasture lands can increase productivity of forage, increase soil health, and reduce nutrient and sediment losses from livestock operations.
ACA and Barnyard Runoff Controls	Agricultural Compliance	Control of runoff from barnyards and animal concentration areas (ACAs) is a required part of agricultural compliance in Pennsylvania.
Manure Storages	Manure Storage Facilities	Installation and use of manure storage systems that have sufficient storage capacity can reduce runoff from barnyards and animal concentration areas and aid in overall manure management on the farm by allowing for more seasonable manure application that maximizes crop nutrient uptake while minimizing environmental loss.
STREAMS/RIPARIAN		
Riparian Buffers	Grassed Riparian Buffers Forested Riparian Buffers	Riparian buffers along streams in both agricultural and urban lands reduce nutrient and sediment loads to streams and provide a variety of other water quality and environmental benefits.
Stream and Wetland Restoration	Stream and Wetland Restoration	Restoration of streams to stabilize eroding stream banks, re-establish floodplain

		connection, and restoration of wetlands. Reduce sediment and nutrient loads, and provide other ecological and natural systems-related benefits. Restoration can occur in both agricultural and urban landscapes, and target infrastructure protection.
URBAN		
Erosion and Sediment Control (E&S) BMPs for Construction	Meet Current Erosion and Sediment (E&S) Control and Post Construction Stormwater Management (PCSM) Requirements	Implementation of E&S BMPs minimizes sediment and nutrient losses during construction activities.
Stormwater BMP Retrofits	Meet Current MS4 Permit Requirements Industrial Stormwater	Stormwater retrofits can target new facilities or existing stormwater BMPs to enhance the ability of such practices to remove pollutants, including nutrients and sediment. Older, more vulnerable systems would be prioritized. They include a variety of different stormwater BMPs. These BMPs can be projects proposed as part of an MS4 Pollutant Reduction Plan or retrofit projects at industrial facilities.
Urban Tree Planting and Conservation Landscaping	Tree Canopy Woods and Pollinator Habitat	Planting trees in developed areas and converting turf to woods and meadows by planting natural vegetation reduces nutrients from urban landscapes.

4. Analytical Framework

Watershed management plans are often evaluated according to their effects on annual average pollution loads assuming a stationary climate and that BMP efficiencies are constant. The Chesapeake Bay Program's analysis of climate change impacts assumed a future steady state climate but assumed BMP efficiencies were unaffected by climate change. Intra-annual responses to weather events, and the implications of these events for BMP choices and efficiencies within the new climate regime were not explicitly considered. Yet, changes in weather variability and effects of climate change on the effectiveness of BMP in new climate regimes are of fundamental importance to the implications of climate change for the planning of local communities and counties within the tiered approach. For example, intensity-duration frequency are indeed shifting upward with increased probabilities of runoff throughout the mid-Atlantic and Northeast (Wright et al., 2010). Based on extensive scenario testing, the 100-year recurrence interval event amounts, the median increase is projected to be between 5 and 10% across New York State for the climate period of 2019-2039 and 10-20% for the high CO2 concentration scenario in the 2040-2069 period (DeGaetano & Castellan, 2017). Clearly, the nature of design storms for BMPs are changing, yet the standard percent reduction efficiencies neglect this increasing variability which will translate to a larger disconnect between estimated and actual nonpoint source pollution reductions.

Research on the effects of climate change on local level planning that takes into account the effects of climate change on variability and the effectiveness of BMPs is very limited, and essentially nonexistent for Pennsylvania. We present in this section analytical frameworks that will facilitate thinking about the vulnerability of BMPs and watershed plans to climate change, provide foundations for qualitative analysis, facilitation identification of management adaptations, and critical information gaps.

4.1 Watershed Management Principles

Effective management for water quality requires balancing watershed scale inputs and outputs of nutrients. Given the massive imbalances in urban and many agricultural landscapes, BMPs are a critically important component of water quality management strategies. Like many strategies, those in Chesapeake Bay rely on a set percent reduction coefficient. There are key advantages of this status quo; especially in ease of use and calculation, but the disadvantages are seen in spatial and temporal variability of actual BMP reductions. The spatial and temporal variability is only set to increase in an environment with longer inter-storm periods and more intense precipitation events. There are many complex relationships and non-linear dynamics associated with these changes on the fluxes of nitrogen, phosphorus, and sediment to local streams and rivers. The status quo conceptual model for water quality management is that BMPs have prescribed percent reduction efficiencies. Based on the number of BMPs without respect to spatial placement, calculations on nutrient reductions to the baseline load are straightforward. However, given the lack of return on investment seen across the nation on TMDL water quality management, new strategies are required to meet water quality goals (US GAO, 2013).

The status quo is based on opportunistic placement of BMPs based on social connections with willing landowners or municipally owned property. However, there could be ideal locations to maximize water quality improvement beyond these limited opportunities and placement that occurs on an ad hoc basis (Figure 1). There is tremendous opportunity to return a better yield on BMP investment by considering the spatial context for BMP placement. Selecting the right BMP installed in the right place has been a recent focus of scientific inquiry (Tomer et al. 2015; McClellan et al., 2018). Ideally, the placement of BMPs occurs within a workflow that prioritizes small watersheds for NPS pollution load, identifies the right practices in the right places, and then predicts what water quality outcomes derive from the portfolio of BMPs. (Figure 1).

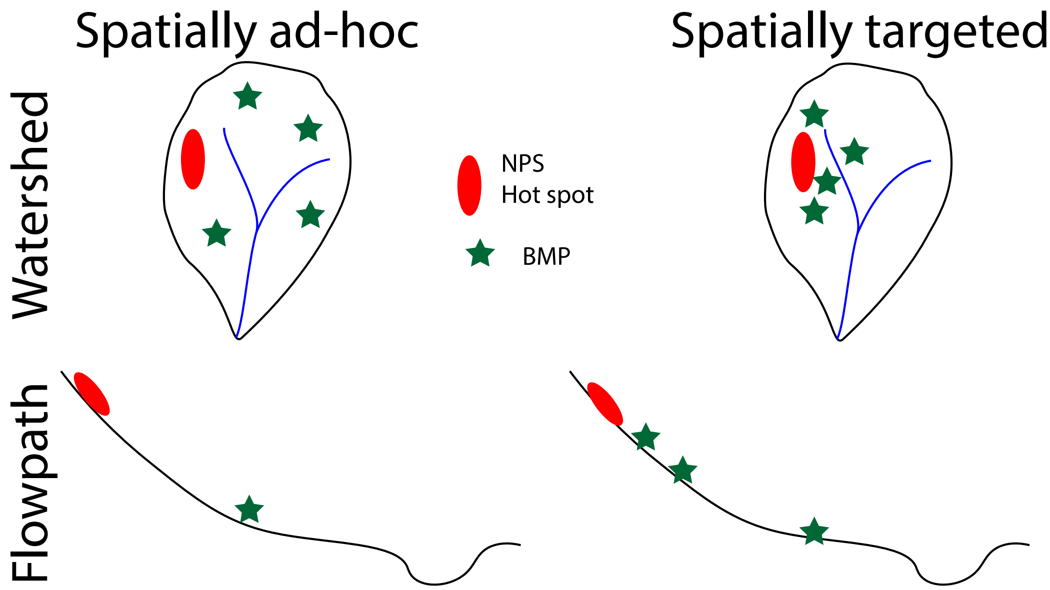


Figure 1. Watershed scale (top row) and flowpath scale (bottom row) conceptualization of opportunistically placed BMPs (spatially ad-hoc) vs. spatially targeted BMPs that are selected based on biophysical properties to maximize nutrient and sediment reductions

Research on nutrient management provides a set of fundamental principles for efficient and effective water quality protection. These include:

- Landscape structure is a key determinant of nutrient loads. Structural features that matter include topography, land cover, and land use. Strategic management requires looking holistically at the landscape and using the best available data to make informed decisions.
- Small scale features of nutrient sources and sinks across the landscape can have significant effects on water quality outcomes. This implies a significant degree of spatial specificity is required for efficient and effective management.
- Landscape heterogeneity results in significant differences in the effectiveness of BMP performance based on site-specific factors within watersheds. This implies that strategic management optimally prioritizes locations in watersheds for the placement of BMPs.
- Heterogeneity of landscapes, farming operations, and urban infrastructure implies variations in the cost effectiveness of BMPs. Here, this implies that strategic management optimally prioritizes practices within watershed locations.

These fundamental principles are general and will be as true for new climate regimes as for existing regimes. However, with increasing variability and intensity of weather, greater understanding of the vulnerability and resilience to evolving climate will be needed to implement these principles. Current understanding of spatial and temporal variations in practice performance is already limited. Research to improve this understanding will be essential for local governments, counties, and other water quality managers to develop plans that will achieve water quality goals with a high degree of reliability at reasonable cost.

4.2 Exposure / Sensitivity / Adaptive Capacity of Climate Vulnerability

Effectively assessing and addressing vulnerability of any sector, program, or management strategy first requires an understanding of the primary factors impacting vulnerability and what influences or controls those factors. One method to organize vulnerability assessments is through a vulnerability scoping diagram (VSD) (Polsky et al., 2017). This assessment tool divides vulnerability into 3 dimensions (Exposure, Sensitivity, and Adaptive Capacity elements), defines the components of the 3 dimensions, and finally describes how those components are measured. Below, general aspects of these vulnerability elements are presented for select BMPs from the four Phase 3 WIP categories identified and are followed by example VSDs. Some general comments on other BMPs in each of the four categories are also provided. A key step in moving from the general aspects to the specific vulnerabilities presented in the VSD examples is explicit identification of the nature of the climate exposure, sensitivity to that exposure, and corresponding adaptive capacities.

4.2.1 CROPS: Nutrient Management

Nutrient management is the application of nutrients (here, nitrogen (N) and phosphorus (P)) to maximize crop yield while minimizing losses to the environment. Nutrient management plays a critical role in reducing nutrients to local surface waters in Pennsylvania and the Chesapeake Bay.

Two forms of nutrient management are recognized for their nutrient reduction benefits in meeting Chesapeake Bay water quality goals: core nutrient management and supplemental nutrient management.

Core nutrient management: Represents baseline nutrient management for N and P.

For N, core nutrient management consists of applying N to crop fields using the following information:

- following land-grant university recommendations (in Pennsylvania, found in the Penn State Agronomy Guide) for N application at the field level;
- if manure is applied, using manure analysis tests or book values to determine nitrogen content;
- calibration of the spreader or applicator used to apply the nutrients;
- yield estimates and cropping plan at the field level; and
- cropping and manure application history at the field level.

For P, core nutrient management consists of applying P to crop fields using the following information:

- following land-grant university recommendations (in Pennsylvania, found in the Penn State Agronomy Guide) for P application at the field level (this may include recommendations resulting from advanced assessments—such as the P index—that recommend higher P application rates where the risk of P loss is low);
- soil tests for P levels at the field level;
- if manure is applied, using manure analysis tests or book values to determine P content; and
- calibration of the spreader or applicator used to apply the nutrients;

Supplemental nutrient management: Ensures that all elements of the core nutrient management practice are met, but additional practices are implemented to "fine tune" N and/or P applications that more precisely align nutrient applications to crop needs, resulting in less loss to the environment. These fine-tuned practices can adjust the *rate* of nutrient application (e.g., at rates below land-grant university recommendations), ensure the *placement* of nutrients is more precise resulting in better nutrient utilization (e.g., injection into the subsurface), or adjust the *timing* of nutrient application (e.g., split applications across the growing season).

Exposure: Exposure for nutrient management is potentially high, given the high season for nutrient management of crops corresponds to the climate change predictions of wetter spring conditions and higher variability and intensity of storm events. Such events may limit conditions for nutrient applications (manure and chemical) and field preparation and planting of crops. More extreme rainfall can also result in increased runoff, which increases nutrient losses prior to plant growth and uptake, which may depress yield and increase losses to the environment, the exact reverse of nutrient management's intended goals.

Sensitivity: As a non-structural, management-based practice, sensitivity is moderate. Nutrient management can still be implemented to meet crop yields and minimize environmental loss in the face of a changing climate. The precise implementation of this practice has always been weather-dependent, and farmers are adept at implementing necessary cropping practices such as nutrient management around variable weather conditions. Yet the advent of more extreme events will challenge farmers' planned nutrient application and planting timelines, and may make it difficult to achieve all necessary field work and precisely time up nutrient application to maximize crop uptake, particularly in spring.

Adaptation: There is a moderately high ability to adapt nutrient management to a changing climate. As a non-structural, management-based practice, nutrient management is inherently implemented through: (i) science-based management standards that guide nutrient management planning, and (ii) management decision making of the individual farmer to guide implementation in the field. Both will need to adapt to a changing climate. Changes in guidance for optimal implementation (e.g., N and P uptake, realistic target yields, etc.) are needed to ensure nutrient management will continue to meet the overall goal of maximizing crop yield while minimizing environmental loss. Agronomic sciences will have to continue to advance to support these changes. In the face of more extreme and varied weather, farmers will have to be even more proactive and nimble to ensure nutrients are applied at times necessary to meet these goals. As farmers begin to pay more attention to nutrient management application decision making, timing and processes, one potential adaptation to Pennsylvania's changing climate may be an increase in the adoption of supplemental nutrient management practices. For example, challenges in spring manure application due to wetter conditions may steer farmers to apply less nutrients in the spring, and then split applications later in the summer growing season, when conditions are drier. High vulnerability to loss of nutrients in high runoff events may support placement-based supplemental nutrient management by adopting setbacks from streams or flow paths that can be critical transport areas of nutrient loss to receiving waters. Subsurface injection of nutrients may also be attractive to prevent nutrient loss in extreme events. Accordingly, there is potential for climate adaptation strategies to increase nutrient reduction potential in the nutrient management arena.

Other Priority Crop Practices: Other priority practices for crop operations specified in the Phase 3 WIP are a variety of structural and management practices (such as grassed waterways, terraces, conservation crop rotations, contour farming) to meet erosion control standards on croplands, no till, and cover crops. All of these practices are field-based and are exposed to climate change. Structural practices such as grassed waterways are particularly vulnerable to increased runoff and concentration of flow that can erode soil and increase vulnerability of vegetation designed to minimize soil loss. Greater flows and intensity of storms can also create vulnerabilities in traditional crop management strategies like conservation crop rotations and contour farming by increasing concentrations of flow and the formation of rill and gully erosion, which may require increased implementation of structural practices like grassed waterways. Design standards for such structural practices may need revised to handle greater and more intense flows. No till and cover crops can be practices that are compatible with many of the impacts of a changing climate and can help crop famers adapt to weather extremes. These practices increase soil organic matter, decrease compaction, and increase soil structure, allowing for quicker equipment access to fields during planting and harvest. No till can also moderate soil moisture extremes during hot summer and drought conditions, mitigating against yield loss. Milder winters allow for increased planting and growth of winter cover crops and double crops, which can increase soil health, provide beneficial ecosystem services, and add to cash crop portfolios (Wolfe et al., 2017). An increase in adoption of no till and cover crops in the face of a changing climate would increase nutrient reductions in very cost effective and resilient ways.

4.2.2 LIVESTOCK: Pasture Management

Pasture management practices that involve prescribed or rotational grazing of livestock can increase productivity of forage, increase soil health, and reduce nutrient and sediment losses from livestock operations. Pennsylvania proposes prescribed grazing on 50% of pasture acreage in the Chesapeake Bay watershed as a priority practice to achieve soil health-based nutrient reductions for livestock operations.

Figure 2*: On the left is an example of good pasture management practices from a dairy farm in southcentral PA. Pastures are fenced into several different paddocks and animals are rotated on a schedule to establish excellent vegetative cover. Streams are fenced out of the pastures and planted with trees to establish a forested riparian buffer. On the right is a pasture along a stream in central PA in need of improved pasture management. The pasture is overgrazed, thus preventing establishment of vegetation, and cattle have direct access to the stream. The right portion of the photo shows flow paths that transport sediment and nutrients during rain events. These management challenges can be exacerbated by climate change.*

Exposure: Exposure for pasture management is moderately high, especially in locations which are perennially wet, poorly drained, and sloped. Pasture lands can exhibit these characteristics since higher productivity lands are often prioritized for crops, while pastures are relegated to marginal lands, many times in riparian zones. While climate change has been predicted to increase grassland productivity in Europe (Chang et al., 2015), more frequent, intense, and variable rainfalls expected in Pennsylvania in the spring have potential to adversely impact pastures, particular during times of active grazing. Livestock can very quickly degrade pastures under such conditions, resulting in loss of vegetative cover, an increase in muddy conditions, and accelerated erosion and loss of sediment and nutrients during frequent storm events. Conversely, hotter and dryer conditions in summer may stifle growth of pasture grasses. For example, hay and forage crops in the northeast United States suffered significant losses in a severe summer drought in the year 2016 (Wolfe et al., 2017).

Sensitivity: As a management-based practice, sensitivity is moderate, though structural elements to the practice make pasture management sensitive to climate change impacts. Grazing managers must be cognizant of wet weather conditions and more proactively manage livestock to prevent pasture damage and sediment and nutrient loss, potentially by moving them more frequently. Incorporating stabilized animal heavy use areas or sacrifice lots into grazing management becomes a higher priority when dealing with wet conditions, so that pastureland can be rested during vulnerable times. Yet short term, structural limitations to manage this sensitivity may exist if a sufficient number of paddocks have not been established or sacrifice lots have not been constructed and sufficiently stabilized to prevent degradation during intense and frequent storm events. Loss of preferred grasses and forage in pastures as a result of grazing during wet conditions can also create pathways for undesirable weed species that depress productivity and viability of grazing and create their own management challenges. Summer heat and drought may also stress pasture grasses, decreasing productivity.

Adaptation: There is a moderately high ability to adapt pasture management to a changing climate. Prescribed or rotational grazing practices can minimize livestock damage to pasture areas during wet conditions. This will require livestock managers to take a more active role in grazing management and move animals more frequently. Adaptation may require investments to implement structural upgrades, such as fencing to ensure adequate paddock numbers and stabilized sacrifice lots. In situations where livestock have degraded pastures during prolonged wet conditions, weed control may become a higher priority. Pastures may even need to be renovated and re-seeded to establish productivity. Managing pastures during extreme heat and drought conditions, while unlikely to increase sediment and nutrient losses from pasture management, may create adaptation challenges for producers in terms of meeting livestock nutrition needs, thus potentially increasing costs of feed supplement.

Other Priority Livestock Practices: Other priority practices for livestock operations specified in the Phase 3 WIP are animal concentration area (ACA) and barnyard runoff controls and manure storages. ACA and barnyard runoff controls are structural BMPs that are exposed to climate change, particularly increased and more extreme wet weather events. Sensitivities to such events do exist, as heavy rainfalls can result in more intense runoff. Use of vegetative swales and filters as part of runoff controls may be vulnerable to erosion, particularly during or just after construction. Maintenance considerations (including maintenance of roof runoff gutters and downspouts and clean water diversions) may be more prevalent. Runoff controls may be designed to discharge runoff to manure storages, which have their own sensitivities with respect to increased rainfall and extreme events. During such events, storages may be vulnerable to overtopping if enough freeboard is not provided. Adaptation through changes in design standards may be necessary to prevent these problems under future climate scenarios.

4.2.3 STREAM / RIPARIAN: Riparian Buffers

Riparian buffers are a key component of the State's BMP portfolio for the Chesapeake Bay and beyond. Buffers are inherently linked to stream restoration but for the purposes of this report are kept separate as stream restoration often cuts down forested riparian buffers in order to alter channel geomorphology.

***Figure 3**: Examples of riparian buffers in agricultural landscapes, Northumberland County PA. On the left is a forested riparian buffer along a first order stream. On the right is a mixed stiff rim grass and forested buffer.*

Exposure: Exposure for riparian buffers is moderately high, especially in locations prone to flooding and invasive species. Flash flooding can severely impact newly planted buffers, but not all buffer sites are likely to be flooded. Invasive species are currently a concern for riparian buffer plantings, a trend that will likely only continue to increase as mean annual temperatures rise. Riparian plants are susceptible to invasive plants for a variety of reasons including deer browse and strong competition for native species (Sweeney & Czapka, 2004; Richardson et al., 2007). Invasive pests such as the hemlock wooly adelgid, emerald ash borer, and now spotted lanternfly are putting additional pressure on native tree species across the Commonwealth.

Ecological assessments of riparian areas in constructed buffers in agricultural landscapes were found to have more invasive vegetation cover than riparian areas in other study locations (Adeyemo, 2018). This increased invasive vegetation cover is likely a result of many factors including frequent disturbance, extremely variable hydrology, and varying levels of site maintenance after construction.

Sensitivity: Like any structural BMP, sensitivities to extreme events do exist. Intense and heavy rainfalls can erode soils, bedding material, and outfall structures. Without sufficient maintenance after heavy rains, some riparian buffers can be damaged, especially in the first years after planting.

Adaptation: There is moderately high ability to adapt riparian buffers in a changing climate. This is primarily in the form of maintenance to keep sites free of invasive or other vegetation than can outcompete planted trees. Keeping deer browse low with proper tubes and erosion minimized is important.

Other Priority Stream/Riparian Practices: Other priority practices for stream and riparian areas identified in the Phase 3 WIP include stream and wetland restoration. While these practices are exposed to climate change, vulnerabilities are dependent on the type of restoration approach and specifics regarding engineering and design. Since such projects typically involve earth moving, placement of stabilization structures, and seeding, mulching and planting of newly disturbed land along streams, these projects may be most vulnerable to extreme weather events during or just after construction, before vegetation has been established and sites are stabilized. Stream bank stabilization structures may also be vulnerable to failure from high flows during extreme events, particularly shortly after construction. Designs that consider an increase in such storm events can help mitigate against these concerns. Opportunities to restore wetlands and reconnect stream corridors with riparian floodplains and wetlands that couple nutrient and sediment reductions with flood mitigation and habitat improvement functions should also be explored as climate change mitigation strategies.

4.2.4 URBAN: Stormwater Retrofits

In developed areas, stormwater solutions often need to be creatively installed around existing infrastructure. Strategies like curb cuts, bioswales, rain gardens, and pervious paving can all play a role in retrofit design.

Figure 4: *Examples of urban stormwater retrofits in Lancaster, PA (July 2019). On the left is a curb extension project that funnels street runoff along the curb and into a step pool infiltration bed. On the right is a large on-street parking lot to rain garden conversion project. It also drains rooftop runoff from the adjacent building.*

Exposure: Exposure for urban stormwater retrofits is potentially high, especially in cities with urban heat island impacts where precipitation intensity can be higher (Ryu et al., 2016). Urban environments exhibit higher peak temperatures, more extreme rainfall, and can have higher amounts of litter, storm debris, and sediment (Brown, 2005) that can decrease BMP efficiency.

Sensitivity: Like any structural BMP, sensitivities to extreme events do exist. Intense and heavy rainfalls can erode soils, bedding material, and outfall structures. Without sufficient maintenance after heavy rains, some rain gardens can also silt in, limiting infiltration capacity and hydrologic functioning during subsequent events.

Adaptation: There is moderate ability to adapt retrofits to a changing climate. In a sense, many retrofits are a form of adaptation themselves. As regulations and design standards change, urban planners and stormwater engineers often have to work and rework drainage designs. By changing soil depth, outfall designs, and vegetation, stormwater retrofits can be marginally adapted for increasingly intense rain events.

Other Priority Urban Practices: Other priority urban practices identified in the Phase 3 WIP include erosion and sediment (E&S) control BMPs for construction, urban tree planting, and conservation landscaping. All of these are exposed to climate change. E&S control BMPs are particularly vulnerable to increased nutrient and sediment discharges during increased runoff events, and increased intensity and frequency of storms may even threaten the integrity of such structures. Modifications in design standards to withstand these impacts may need to be explored. Increased rainfall may however potentially improve survivability of tree plantings and conservation landscaping in the urban sector. Hotter, dryer summers may impact survivorship of new plantings, however. Yet milder falls and winters may allow for successful plantings later in the season. Particular attention to the changing seasonality of plant-based restoration practices is warranted in the face of a changing climate.

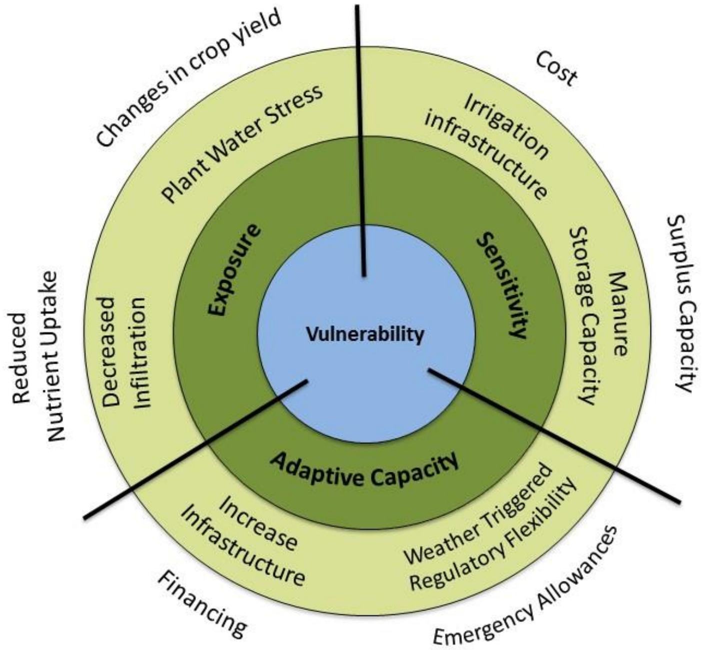
4.2.5 Vulnerability Scoping Diagrams (VSDs) for Selected BMPs

To effectively use the VSD to assess the vulnerably of a program or practice of interest, there must first be a specific definition of the hazard and the focus of the hazard (e.g., vulnerability of what to what). For example, in recent work assessing the vulnerability of Mid-Atlantic wetlands to climate change (Wardrop et al., 2019), wetland hydrogeomorphic (HGM) type, ecoregion, time of year, and climate drivers all needed to be defined because landscape position, regional geography, land use, seasonality, and precipitation patterns all influenced vulnerability.

Four example VSDs are provided below describing the vulnerability of a specific practice selected from each of the Phase 3 WIP categories listed in Table 1 to a specific climate change driven stressor (Figure 5). Based on results from earlier work and the variability of projected precipitation changes across the state, these examples may benefit from additional information such as ecoregion, resource availability, or surrounding land use patterns to adequately create a framework to assess vulnerbility.

Vulnerability of:
Type: CROPS
BMP: Nutrient Management

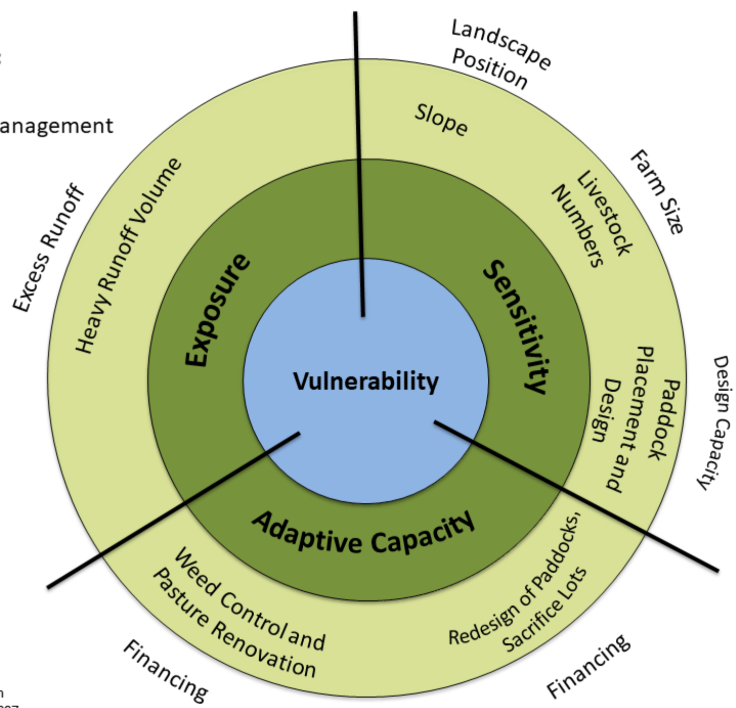
To: Drier Summers



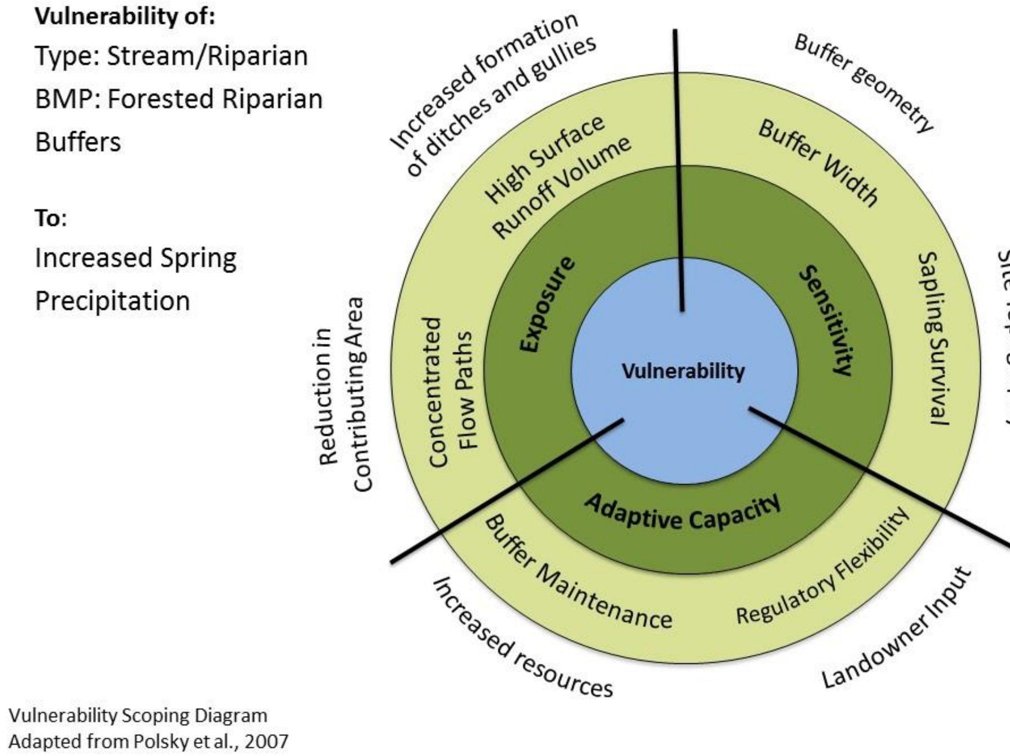
Vulnerability Scoping Diagram
Adapted from Polsky et al., 2007

Vulnerability of:
Type: Livestock
BMP: Pasture Management

To:
Intense Rainfall



Vulnerability Scoping Diagram
Adapted from Polsky et. Al, 2007



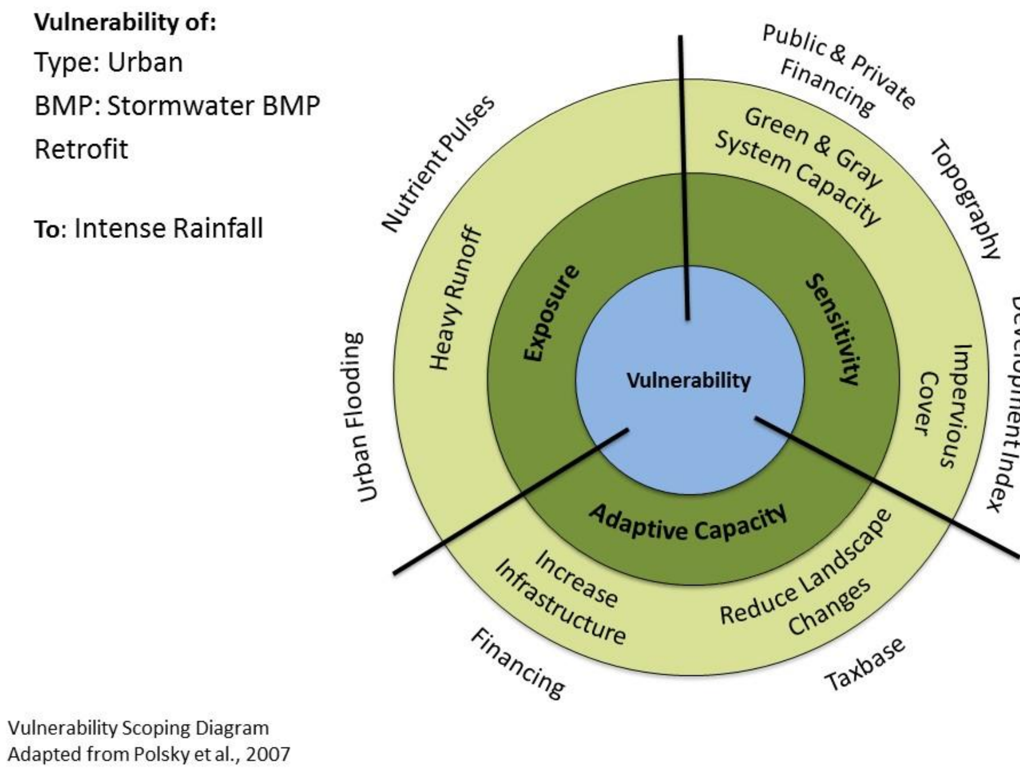


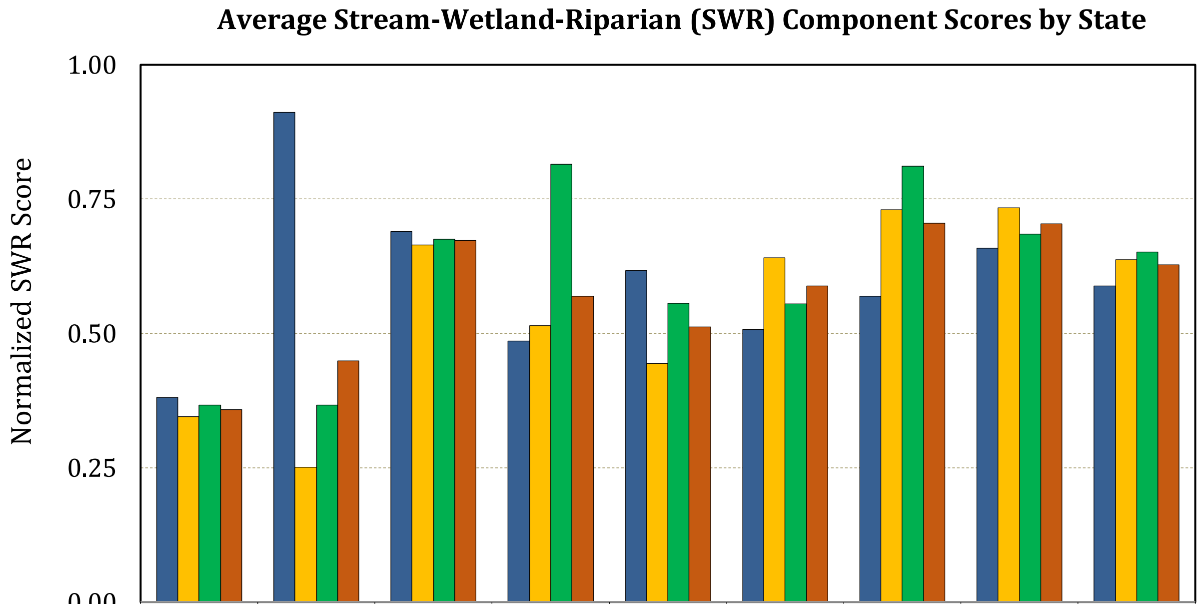
Figure 5: *Example vulnerability scoping diagram (VSD) of BMPs in four BMP categories.*

5. CASE STUDIES

5.1 Case Study: Ecological Condition Assessments of Forested Riparian Buffers

Forested riparian buffers provide a wide array of ecosystem services impacting water resources including nutrient cycling, *floodwater* retention, wildlife habitat, carbon storage, and stream canopy shading. In the Chesapeake Bay watershed, the USDA's Conservation Reserve Enhancement Program (CREP) has successfully enrolled over 20,000 privately owned streamside forested buffer contracts into this voluntary program. CREP focuses on reducing delivery of nutrients and sediment from upland agricultural landscapes before these pollutants reach streams and ultimately impact the Bay, but also aims to improve local water quality and riparian ecosystems throughout the Bay watershed. A recent USDA/Penn State report (Kleinman et al., 2019) utilizing both modeling and site assessments across 149 CREP contracts in Pennsylvania, Maryland, and Virginia found the forested riparian buffers are successfully reducing erosion and nutrient transport.

The buffer evaluation included ecological condition assessments of 79 forested buffer sites in Pennsylvania using the Stream-Wetland-Riparian (SWR) index, which incorporates factors including buffer width and cover, invasive vegetation, stream stressors, floodplain and wetland (FL_WL) stressors, stream habitat assessment (SHA), basal area, and bank incision (Brooks et al., 2009). These site assessments found little difference between the overall condition of Pennsylvania buffer contracts and sites in other states, with the average CREP buffer in Pennsylvania scoring in the 2nd highest condition tier (sub-optimal). Pennsylvania buffers had slightly higher stream stressor scores, indicating fewer in-stream stressors were observed than in the other states in the study, and averaged the highest stream habitat assessment scores. Basal area scores for buffers in Pennsylvania were generally lower than in other states, indicating fewer saplings surviving in Pennsylvania forested buffer sites. (Figure 6)



	Buffer Score	Basal Area	Invasive Plants	FP-WL Stressor	FP-WL Condition	SHA Score	Incision Ratio	Stream Stressor	FINAL SWR
CREP MD	0.38	0.91	0.69	0.49	0.62	0.51	0.57	0.66	0.59
CREP PA	0.34	0.25	0.66	0.52	0.44	0.64	0.73	0.73	0.64
CREP VA	0.37	0.37	0.68	0.82	0.56	0.55	0.81	0.69	0.65
CREP All Sites	0.36	0.45	0.67	0.57	0.51	0.59	0.71	0.70	0.63

Figure 6: Average SWR component and final scores for CREP riparian forest buffers in Pennsylvania, Maryland, and Virginia. Kleinman et al., 2019.

Although this study found CREP buffers to be successful fulfilling many of the program's objectives, specifically reducing nutrient delivery to the Bay, the combined modeling and site assessment effort identified areas that could be improved to increase buffer function. A widespread issue, short-circuiting of riparian buffers, occurs when runoff from the landscape is concentrated into narrow areas, creating ditches or gullies during large rainfall events. This short-circuiting reduces the contributing landscape area treated by the buffer and creates a direct connection between potential sediment and nutrient source areas and the stream channel. A supplemental publication to this report (Wallace et al, 2018) included modeling of 3 Long-Term Agricultural Research (LTAR) watersheds in Pennsylvania (Spring Creek, Conewago Creek, and Mahantango Creek). This study highlighted the short-circuiting issue using topographic openness data (Figure 7) to identify concentrated flow paths and calculate the reduction in the landscape area treated by riparian buffers. Short-circuiting by gullies and ditches in the 3 Pennsylvania LTAR watersheds selected for this study reduced the treated area in the landscape by 22-54%.

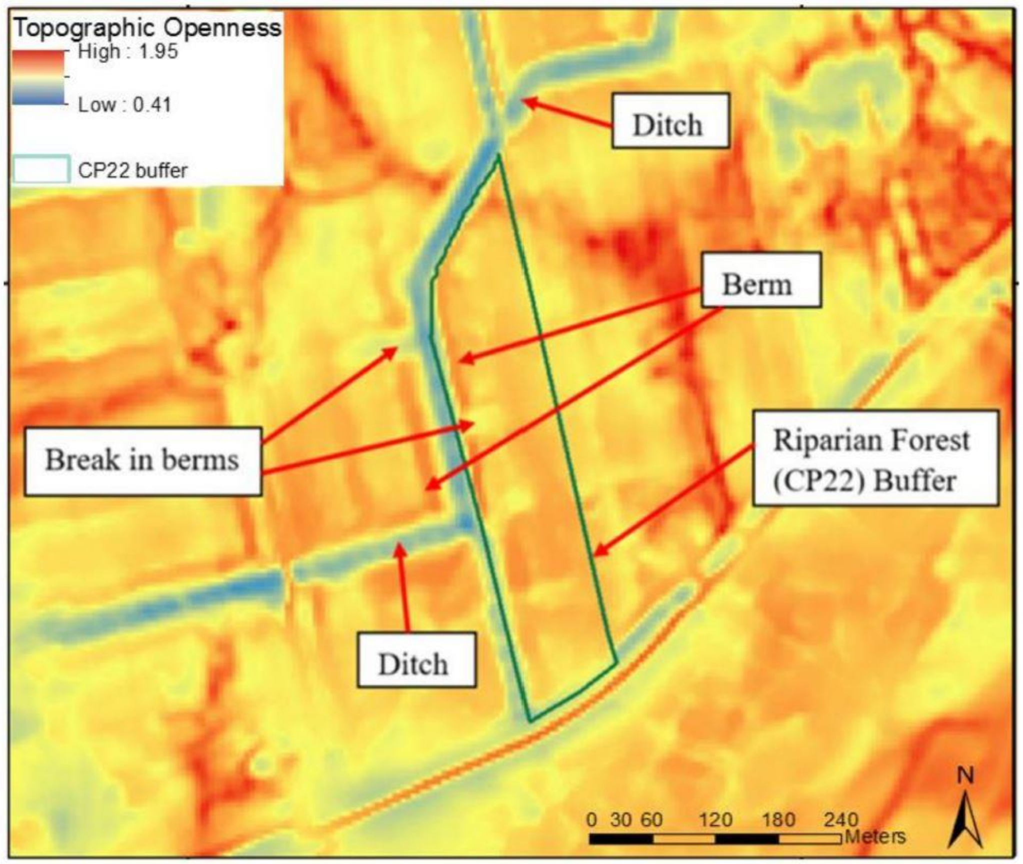


Figure 7: A close-up of hydrologic features such as berms and ditches identified using topographic openness. Wallace et al., 2018.

Many of the recommendations outlined in the CREP Observations, Assessments, and Recommendations document align with climate-smart adaptation strategies. For example, variable width buffers would focus CREP resources on areas of the landscape with the most need to treat surface runoff while simultaneously minimizing the amount of land removed from active agriculture production. This strategy also builds climate resiliency into the buffer, as more frequent and intense surface runoff generating events will be better handled by buffer systems designed to treat areas of concentrated flow using larger buffer widths. Another strategy to build climate change resilience into buffer management is to locate buffers in groups or clusters with other BMPs. This utilization of BMP suites will more broadly distribute the amount of runoff any single buffer could effectively process across multiple systems that are more capable of effectively handling large runoff events. Ultimately, building climate change resilient buffer systems will not require new instrumentation or radical changes to current management strategies, but refinements to existing guidelines and strategic decision making will differentiate future buffer successes from failures.

Strategies such as variable width buffers and BMP suites are not isolated to boosting climate change resiliency or improving nutrient management plans. These recommendations align with both the original goals of the CREP program, and the current realities of CREP buffer systems across Pennsylvania. Riparian buffers are frequently tasked with performing double duty as both agricultural runoff treatment features and urban stormwater storage areas. This multi-function job description is the result of increasingly mixed land use patterns in traditional agricultural areas, specifically in the southeastern counties of Lancaster, Adams, and Franklin.

5.2 Case Study: Assessment of Riparian Conservation Buffers in Pennsylvania

5.2.1 Location and Distribution

Riparian forest buffers are a highly preferred conservation practice in the Susquehanna-Chesapeake Bay Watershed, in the Mid-Atlantic Region of USA. This watershed comprising 165,800 km^2, supports one of the largest and most productive coastal ecosystems worldwide. A variety of federal, state, and private initiatives promote the installation of riparian buffers mainly to improve water quality, wildlife habitat enhancement, and erosion control. After installation, riparian buffers are considered fully effective in curtailing nutrients, sediment, pesticides, and other pollutants from surface runoff and subsurface flow by deposition, plant intake, and denitrification, among other processes (Kleinman et al, 2019). In fact, riparian forest buffers established according to accepted conservation practice standards, have been recommended as one of the most effective tools for mitigating nonpoint source pollution. Recently, the focus has been on assessing the role of riparian buffers to meet goals established by the Total Maximum Daily Load (TMDL) for the overall Chesapeake Bay Watershed (Kleinman et al, 2019).

Efforts seek to improve the effectiveness of buffer site location, design, and maintenance. A better understanding of surrounding areas, upslope and upstream conditions is key to improve the performance of CREP buffers (Conservation Reserve Enhancement Program). It was found from previous studies that streams flowing through mature forest riparian buffers, provide much higher floodwater retention and service than streams and riparian buffers with only grass or no buffers at all (Kleinman et al, 2019). The increased frequency and seasonality of extreme weather events, such as greater rainfall intensity, will increase the variability of runoff events. Thus, adjustments in conservation practices may be necessary to mitigate the effect of these changes.

To better understand potential negative impacts of climate change and how the different areas are prepared for these changes, a landscape assessment of existent CREP riparian forest buffer projects was conducted within eight counties in the Commonwealth of Pennsylvania and the Susquehanna-Chesapeake Watershed (**Figure 8**). The eight counties were selected based on their pollution reduction and water quality planning goals for the Pennsylvania's Chesapeake Bay watershed. In 2017, a four-tier classification system was defined, based on the opportunity to improve water quality in the watershed through nutrient reductions (PADEP, 2019). Each tier is assigned 25% of the total planning targets for Commonwealth of Pennsylvania. Consequently, the eight selected counties were classified within the following tiers:

Tier System	**County***
Tier 1 (refers to the first 25% of load reduction efforts)	Lancaster, York
Tier 2 (refers to the second 25% of load reduction efforts)	Centre, Franklin
Tier 3 (refers to the third 25% of load reduction efforts)	Adams, Bradford, Columbia
Tier 4 (refers to the last 25% of load reduction efforts and allows Pennsylvania to meet its overall nutrient reduction goals)	Montour

* A complete list of counties per tier can be found in the Pennsylvania Phase 3 Chesapeake Bay Watershed Implementation Plan (PADEP, 2019).

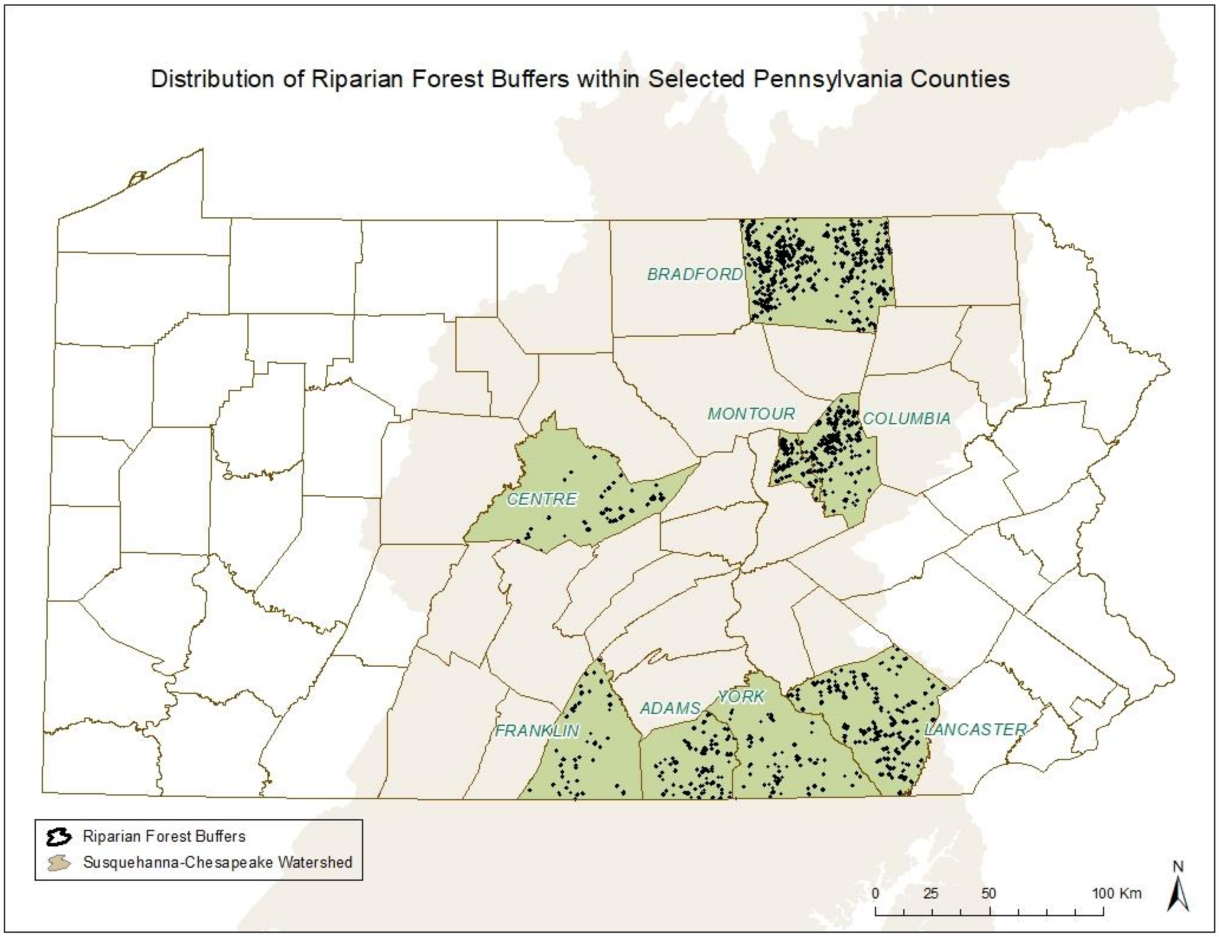


Figure 8. Distribution of riparian forest buffers within selected Pennsylvania Counties.

The distribution of riparian forest sites according to total and mean area per county are presented in **Figure 9**. Individual buffer areas ranged on average from 0.7 to 1.7 ha per county. Bradford County showed the highest total and average area of riparian buffers per county. However, when comparing total buffer area per hectare (m^2/ha), Montour County exhibited the best ratios, followed by Bradford and Columbia (**Figure 10**, blue bars).

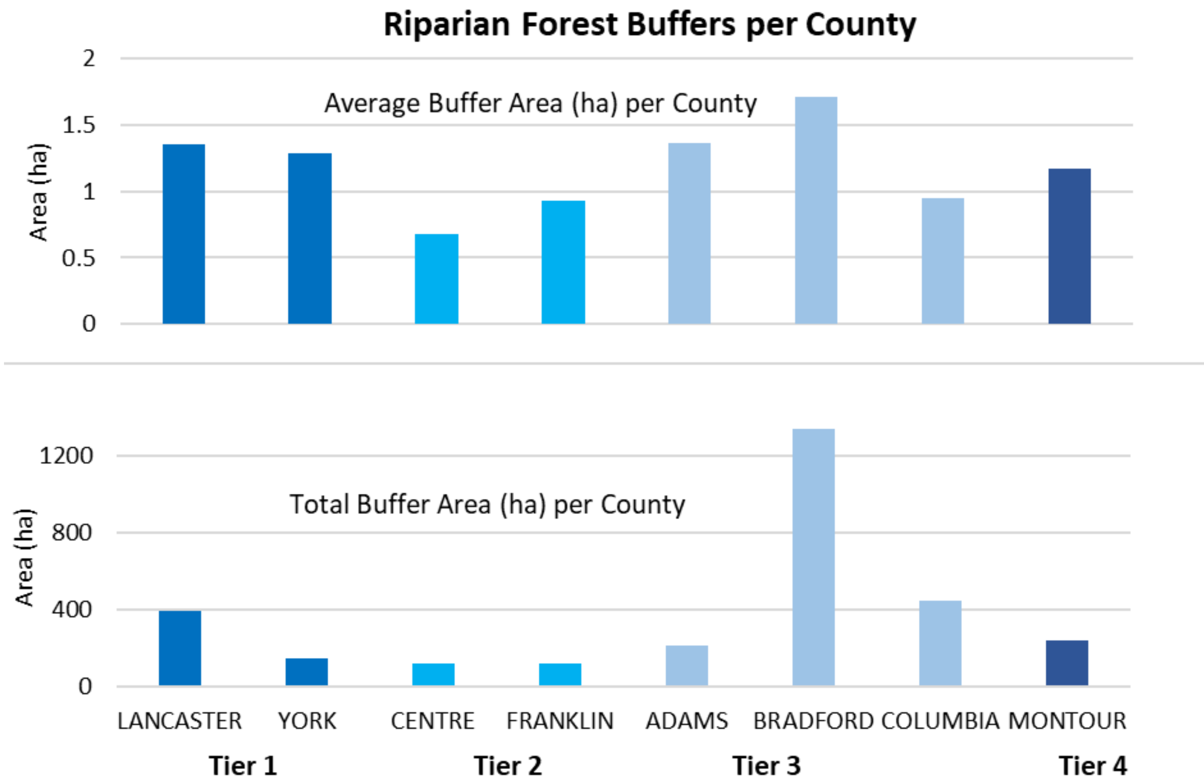


Figure 9. Riparian forest buffers per county sorted by tier 1 (Lancaster and York), tier 2 (Centre and Franklin), tier 3 (Adams, Bradford, and Columbia) and tier 4 (Montour).

Riparian Forest Buffers vs. Other Conservation Practices

Among the many conservation practices (more than 40) within the Conservation Reserve Program (USDA-FSA), the installation of riparian buffers seemed favored in the counties of Adams and Lancaster, where 50% of all conservation practices corresponded to riparian forest buffers (**Figure 10**). However, for the studied counties, it seems that Montour (Tier 4), Bradford (Tier 3), and Columbia better promoted the installation of conservation practices, resulting in higher total area of buffers per hectare. Montour County presented the highest hectare (more than 400 m^2/ha), suggesting significant support for conservation practices. These results are relevant as conservation practice buffers act as filters by trapping sediments and pollutants and consequently improve water quality and sediment control. Converting larger areas to conservation practice buffers will help build resilience to future adverse climate events.

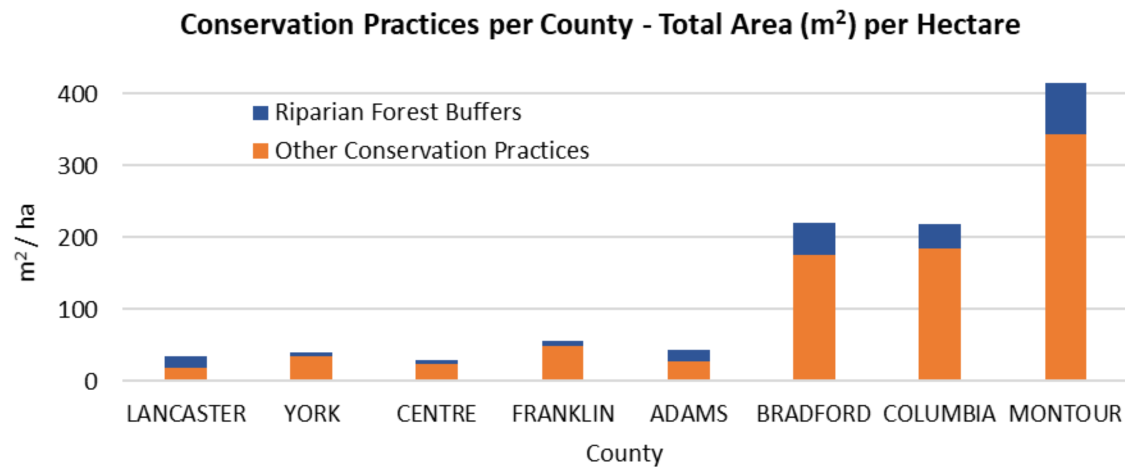


Figure 10. Total area of riparian buffer sites (m^2) per county area (ha).

5.2.2 Landscape Composition: Comparative Analysis (1992-2011)

In addition, a comparative analysis for the years 1992 and 2011 of riparian forest buffers (1,190 sites in total) and surrounding landscapes was conducted to define disturbances resulting from human activity. Centroid points were created for each riparian buffer polygon, and landscape areas were defined as 1-km radius landscape circles around each centroid. In order to avoid spatial dependency, overlapped site areas were eliminated for the landscape assessment. A landscape development intensity (LDI) index was quantified by integrating land cover information (NLCD, 2011).

The LDI index for land use, defined as a human disturbance gradient applied to landscape units, was developed as a landscape-scale assessment tool of wetland condition in Florida (Brown and Vivas 2007). It is calculated by multiplying land use percentages with a weighted factor per land use as shown in equation 1 (Brown and Vivas, 2005),

$$LDI_{Site} = \sum \%LU_i \ x \ LDI_i$$

Where LDI_{site} is the LDI score for landscape circle (wetland site), $\%LU_i$ is percent of total area in land use i, and LDI_i is the landscape development intensity coefficient for land use i. The LDI coefficients used in this study, initially obtained from Brown and Vivas (2005), were adapted by Laubscher et al. (2007) in central Pennsylvania (Table 1).

Table 2. Suggested LDI coefficients per land use.

NLCD Land Use Classes	LDI Coefficients[1]
Water	1.00
Developed/Open Space	7.18
Developed/Low Intensity	7.18
Developed/Medium Intensity	8.97
Developed/High Intensity	8.97
Barren Rock/Clay/Sand	7.81
Forest (Deciduous, Evergreen, Mixed)	1.00
Shrub/Scrub	1.00
Pasture/Hay	3.31
Cultivated Crops	5.77
Wetlands	1.00

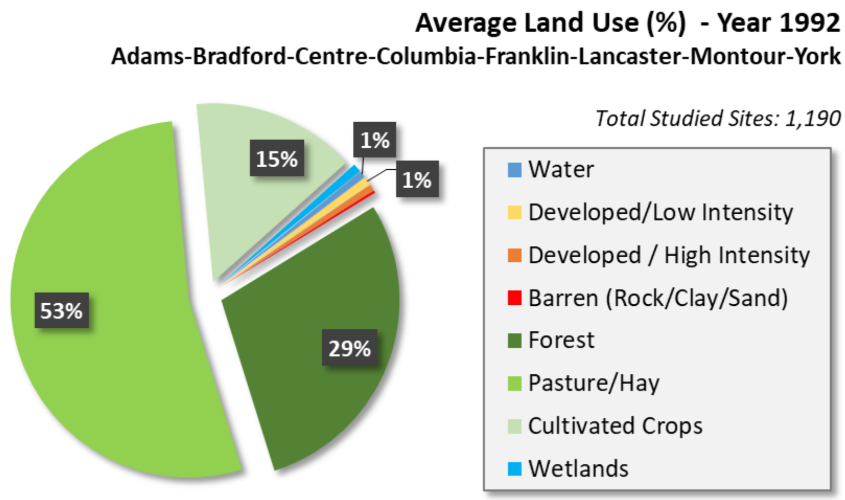
(1) Adapted by Laubscher et al. (2007) from Brown and Vivas (2005). LDI coefficient is calculated as the normalized (on a scale of 1-10) natural log of energy (embodied energy) per are per time

Defined ecological thresholds, i.e., points at which abrupt changes occur in an ecosystem provoked by disturbances (Groffman et al. 2006), were used for this analysis. It is reported that a LDI score of < 2.0 indicates minor agricultural and urban land uses, while > 5.0 indicates urban land uses as the predominant activity and greater disturbance (Brown and Vivas 2005). LDI can be classified according to the following categories:

- LDI > 5 Primarily urban (lowest ecological condition category)
- 2 < LDI < 5 Primarily agricultural
- LDI < 2 Primarily forested (highest ecological condition category)

On average, during the period 1992-2011, the major variation in riparian buffers (1-km circle landscape areas) for the eight selected counties occurred in crop and pasture lands. Areas occupied by croplands doubled in size, covering 15% of total land cover in 1992 and 30% respectively in 2011. On the contrary, pasture and hay land uses decreased from 53% to 30%

during the same period. New developed areas also showed variation, increasing from 1% in 1992 to 7% in 2011 (**Figure 11**).



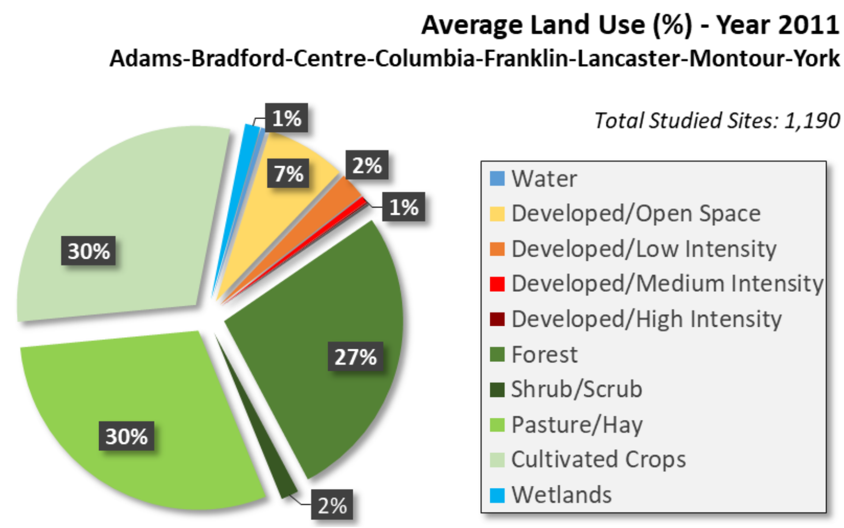


Figure 11. Average land use per county from years 1992 and 2011. Land use was extracted based on 1 km-radius area for each riparian forest buffer.

Total forest for the studied sites within the selected counties practically kept the same area, with just a 2% reduction in average, during the 20-year period. However, variation occurred among counties. Total forest increased for Centre and Franklin Counties (7 and 3%, respectively) while decreased for all other counties (5% in average) (**Figure 12**).

In addition, core and edge forest were analyzed in this preliminary study. It is important to note that quantity of forest is not equal to quality of forest. The identification of edge areas (i.e. forest areas less than 100m from any nonforest edge or opening) is fundamental to determine potential disturbances within a forest. Hence, Fernandez et al. (2019) found the existence of fragmented landscapes, when assessing all surrounding wetland landscapes in PA. They observed on average only 38% of the total forested area was classified as core forest. Accordingly, a high percentage of forested area (62%) is at risk of being disturbed or degraded in PA because it is next to other land uses, i.e., mainly agricultural row crops or pastures (Fernandez et al, 2019). These observations are relevant given the constant loss of core forest experienced through the years in the United States (more than 12% average from 2001 and 2011) and increase of patchy forest (USDA Forest Service 2014).

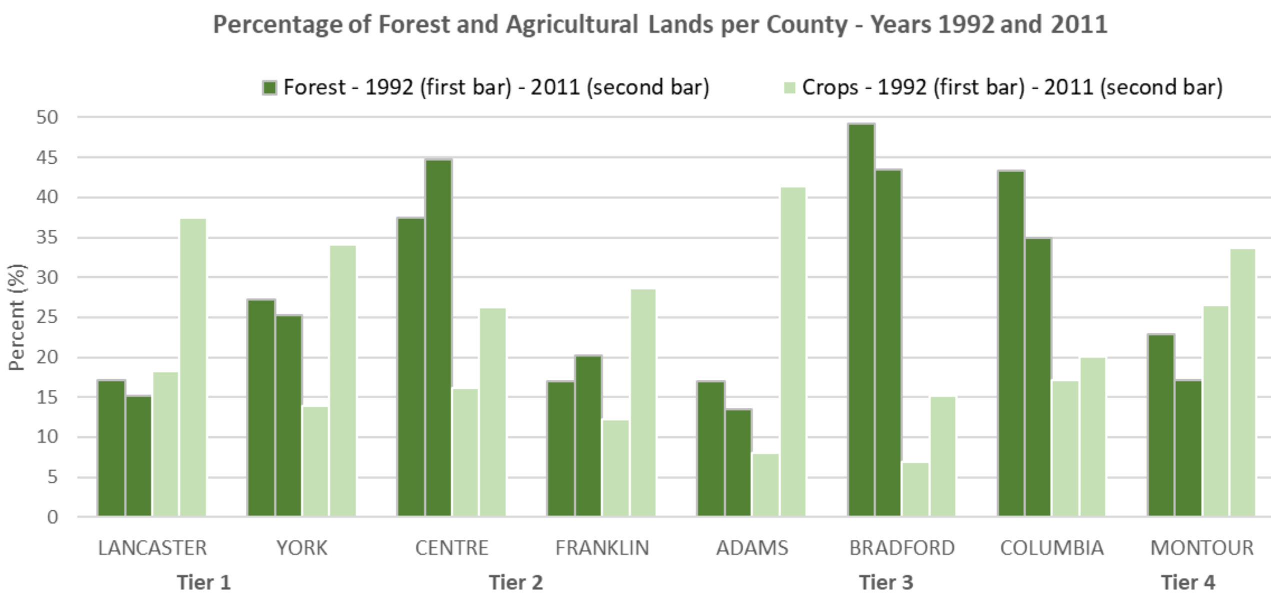


Figure 12. Percentage of forest and agricultural lands per county for the years 1992 and 2011.

For the period 1992-2011, a higher agriculture increase was observed in the riparian landscape circle areas for the counties of Franklin, Lancaster, York, and Adams, varying from >15% to >30%. Special attention should be considered when extreme weather events occur, since these lands could become more vulnerable and less effective to curtail processes such as surface runoff and soil loss.

5.2.3 Landscape Assessment – Year 2011

Based on ecological thresholds, results revealed a large variation in the Landscape Development Intensity (LDI) index within the areas surrounding buffers in the selected counties. Mean LDI values ranged from 2.9 to 4.4 within the studied counties, describing sub-optimal conditions categories, i.e., primarily agriculture (**Figure 13**). The establishment of riparian buffer areas within agricultural zones, as the CRP program promotes, was found to improve the hydro-morphological status of waterbodies. Good hydromorphological conditions support aquatic ecosystems, providing physical habitat for biota such as fish, invertebrates and aquatic macrophytes (USEPA, 2009).

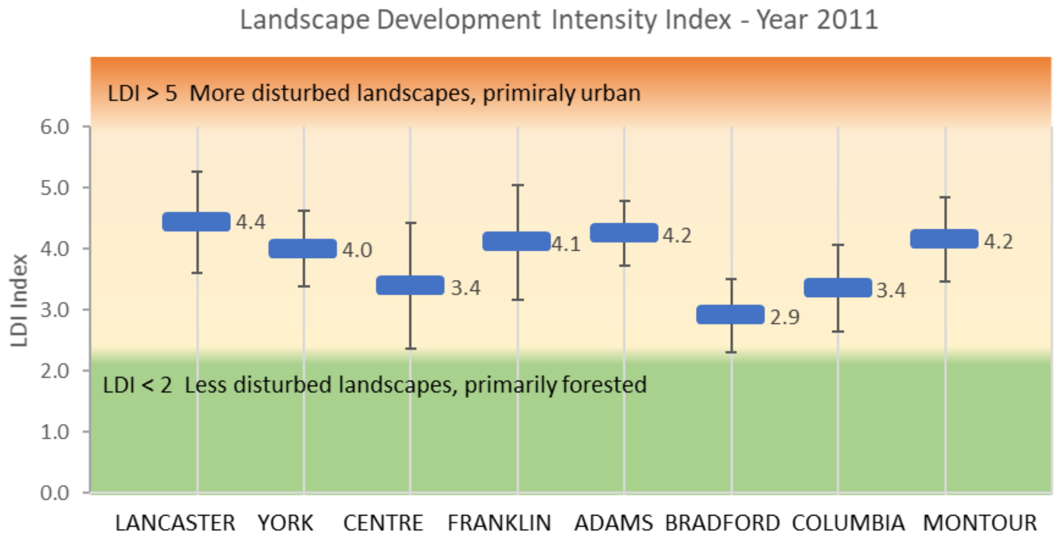


Figure 13. Average Landscape Development Intensity Index per County. Bars are standard deviation of the population.

Special attention was given to Centre County. Although forested areas for Centre County increased by 7% during the studied period, agricultural lands also increased by more than 10%, generating greater disturbances and reducing site ecological conditions in general. Other preliminary landscape assessments done for surrounding wetland sites (1-km circle areas) located within Centre County indicated a worsening of average site ecological condition during the period 1992-2011. When comparing LDI scores from years 1992 to 2011, landscape circle areas with LDI <2 decreased by 11.2%, areas with 2 < LDI < 5 increased by 7.6%, and areas with LDI > 5 increased by 3.6% **(Figure 14)** (Glines and Fernandez, not published).

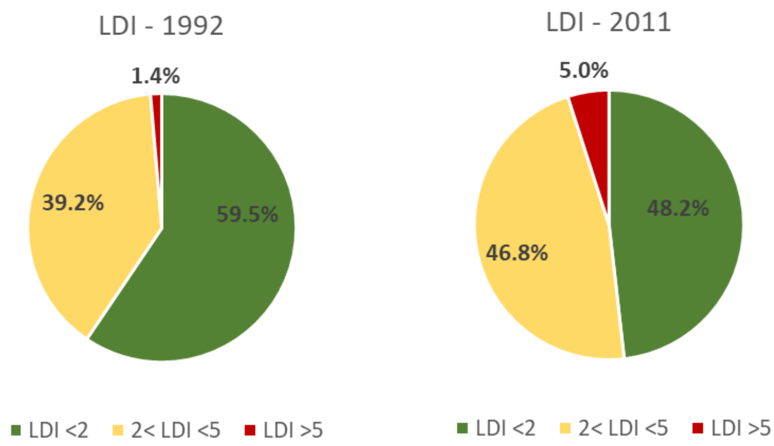


Figure 14. LDI mean values for riparian forest buffer in Centre Country for the period 1992-2011.

Landscape patterns and structural characteristics of riparian buffers are important to determine how well buffers are capable of functioning at a given location. Kleinman et al. (2019), studying riparian buffers in the Susquehanna-Chesapeake watershed, concluded that prioritizing riparian forest buffer location in specific areas within a watershed offers significant benefits for water quality and control of surface runoff. Size, variable buffer width based on converging areas, slope, upslope runoff area, and soil type among others, must be considered when installing new buffers. Hence, understanding not only the site condition, but also the upslope contributing areas and upstream conditions will enhance targeting of buffers, thereby improving effectiveness (Kleinman et al. 2019). Landscape position within a watershed is also relevant when considering effectiveness of riparian buffers. Fernandez et al. (2019) found disturbances and landscape fragmentation occurring at the upper reaches of watersheds throughout different regions in Pennsylvania. These disturbances and fragmented landscapes were observed in areas closer to first order streams with <47% of forest cover and >20% of cultivated crops for the year 2011.

In summary for the period 1992-2011, varied landscape composition and patterns were observed in the different studied counties. Agricultural areas increased in higher proportion during the period, from 15% of total area to 30%. These changes may affect the effectiveness of riparian forest buffers to respond to adverse climate effects. Indicators of human activity (LDI index) also demonstrated the existence of more disturbances in the surrounding landscapes, and a decline of ecological condition categories for the year 2011.

5.3 Case Study: Freshwater Wetland Vulnerability

Recent work focusing on the vulnerability of freshwater wetlands to climate change (outlined in Wardrop et al., 2019) showed variable hydrologic responses to climate change both within watersheds and among watersheds across the state. Groundwater data generated by the Penn State Integrated Hydrologic Model (PIHM) (Qu and Duffy 2007, Bhatt et al., 2008, Yu et al., 2015) indicated landscape heterogeneity influenced groundwater response to changes in temperature and precipitation in both riparian and upland areas **(Figure 15)** Additionally, model results indicated a magnification of seasonal groundwater patterns, with summer groundwater lower and spring groundwater higher than historic levels. This magnification of seasonal changes mirrors the hydrology response to development and increased impervious surfaces and has been linked to degradation of riparian wetland condition and plant community composition (Hychka et al., 2013). **Figure 16** illustrates the magnification of seasonal groundwater fluctuations between spring and summer levels for 3 wetland types in Pennsylvania. Data generated by PIHM for future climate scenarios indicates these seasonal changes will be larger than the signal observed in wetlands with nearby development and other landscape stressors.

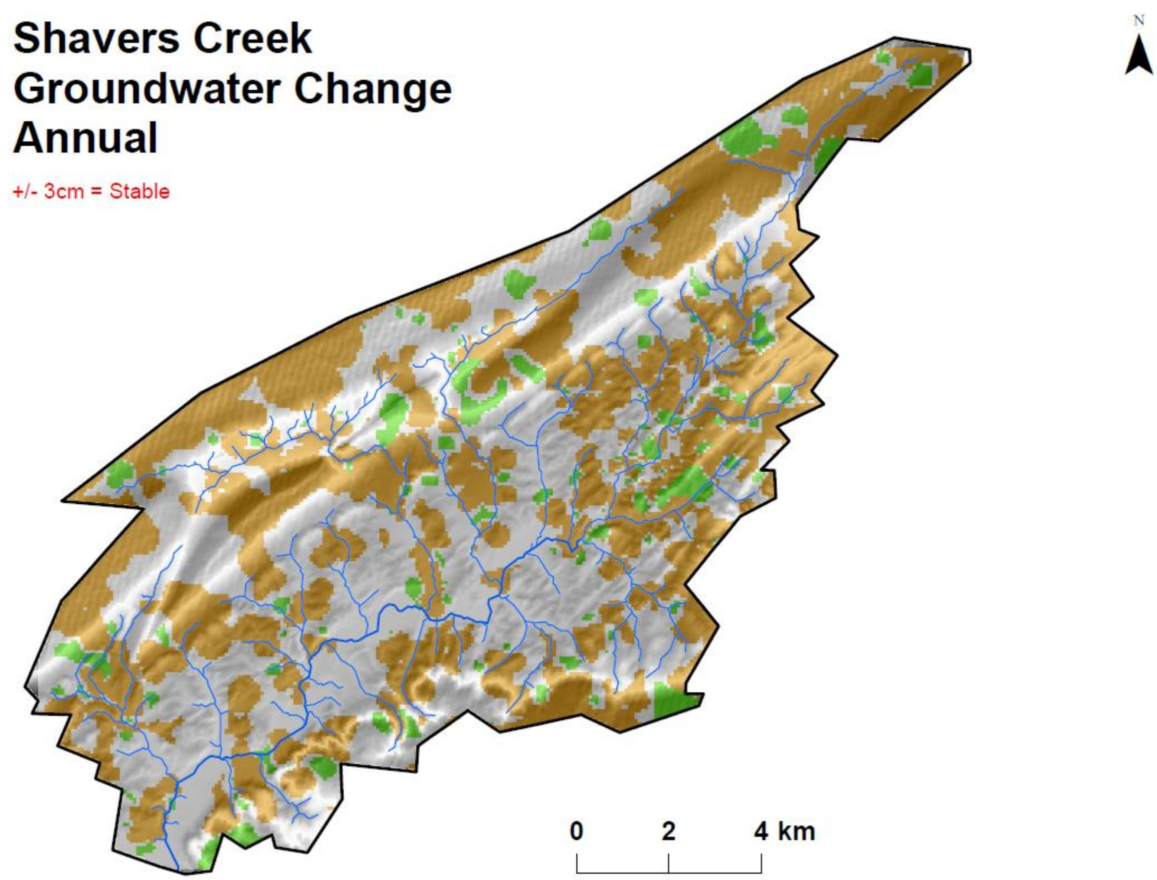


Figure 15: Annual groundwater level differences between 20-year average historical (1979-1998) and future climate scenario (2046-2065) based on the SRES A2 emissions experiment using the MRI-CGCM2.3.2 climate model. Orange indicates groundwater levels have dropped at least 10% of the rooting zone depth (3cm) and green indicates groundwater levels have risen at

least 10% of the rooting zone depth. Data generated using the Penn State Integrated Hydrologic Model.

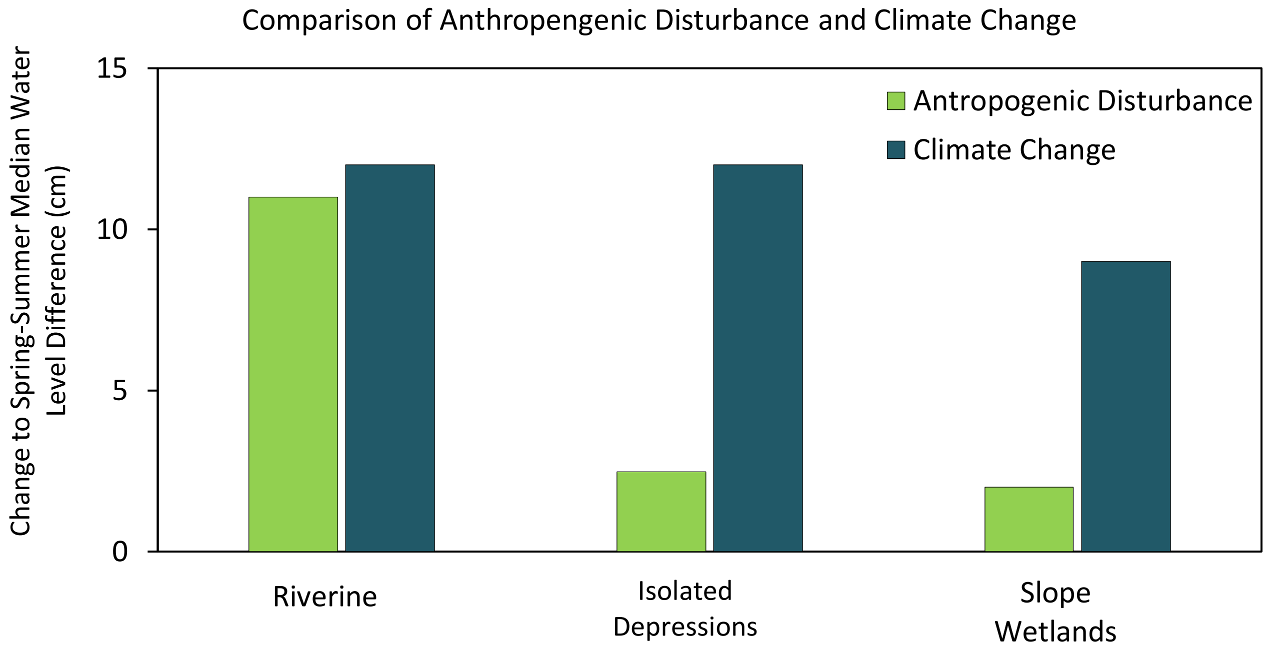


Figure 16: Comparison of differences in spring–summer median water levels resulting from anthropogenic disturbance and climate change. Values for anthropogenic disturbance represent the increase observed between pristine and disturbed wetland sites. Values for climate change represent the increase observed between historic and future climate scenarios. The riverine value for anthropogenic disturbance is derived from single reference standard wetland and is plotted as an absolute value of change. Wardrop et al., 2019.

6. CONCLUSIONS

Climate change will have numerous impacts on water resources and management strategies across Pennsylvania. These potential impacts range from decreases in macroinvertebrate populations (Nukazawa et al., 2018), loss of native brook trout due to warming water temperatures and competition of more thermal tolerance species (Argent et al., 2019), and invasive insects like the Hemlock Woolly Adelgid changing the landscape surrounding headwater streams. Additionally, changes to temperature and precipitation patterns will impact nonpoint pollution and the management strategies used to reduce the delivery of sediment and nutrients from agricultural and urban landscapes to waterways across the Commonwealth. These changes may impact the magnitude and frequency of large precipitation events, resulting in decreased effectiveness of BMPs.

Adjustments to BMP design and location will be needed to mitigate increased and more frequent runoff events, and the spatial variation of climate change impacts within watersheds and across the state will require strategic distribution of resources to prioritize critical locations and watersheds. Climate change may also impact the efficiency of some BMPs, necessitating BMP evaluation criteria focusing on this potential reduction in performance as well as overall resilience to specific climate change impacts. Structural BMPs may also be more vulnerable to the impacts of climate change than non-structural BMPs, as adaption strategies will need to be incorporated into design standards and criteria identifying long-term placement and maintenance. Management plans building resiliency into BMPs will require cost-effective, spatially strategic smart strategies to maximize the impact of resources and provide flexibility to heterogenous landscapes and site-specific challenges. Finally, use of the best available data and modeling results should be part of all new BMP design and maintenance plans to ensure limited resources are utilized in the most efficient and impactful way.

Data needs: There are many unknowns with respect to BMP effectiveness in a changing climate. Simple percent reduction efficiencies will likely deviate with different antecedent conditions and altered storm intensity and magnitudes. A more complete BMP database capturing dynamic efficiencies will be required to explain actual nutrient and sediment reductions.

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Chapter 3 Climate Change and Pennsylvania's Infrastructure*

Seth Blumsack, Doug Wrenn, Wenjing Su

1. Introduction and Summary

As the climate in Pennsylvania is projected to change over the course of the present century, the ways in which weather and other events related to the climate affect major infrastructures is also likely to change. Some types of impacts on infrastructure, particularly those related to flooding and extreme heat, are likely to increase. Other types of impacts, particularly those related to extreme cold, may decrease as Pennsylvania becomes warmer. The entities that plan and operate infrastructure in Pennsylvania, whether they are public entities or private industry, are likely to need to adapt physical infrastructure to a changing climate.

Pennsylvania's infrastructure systems – its energy, transportation and water networks – are both regionally and nationally important. Pennsylvania is the largest exporter of electric power in the U.S., and is becoming a nationally and globally important exporter of natural gas. Infrastructure networks for these energy commodities support Pennsylvania's large energy economy. Pennsylvania also receives large shipments of crude oil and other goods via railways, barges and (in the case of oil and refined petroleum products) pipelines.

These large-scale infrastructure systems support national, regional and local delivery of many commodities, but also support other public and private infrastructure services in Pennsylvania, including wastewater treatment, agriculture and financial services. Figure 1 shows how a single event (flooding related to heavy precipitation or storm surge) could directly impact multiple infrastructures in Pennsylvania, with secondary impacts cascading between highly interdependent infrastructure systems. For example, inland flooding may directly affect electric power system infrastructure, the ability of transportation infrastructures to move fuel and other goods, and may trigger landslides. Failures in the electric power grid, for example, may arise directly from flooding (if substations are submerged or affected by storm surge) or indirectly as the fuel transport system is affected.

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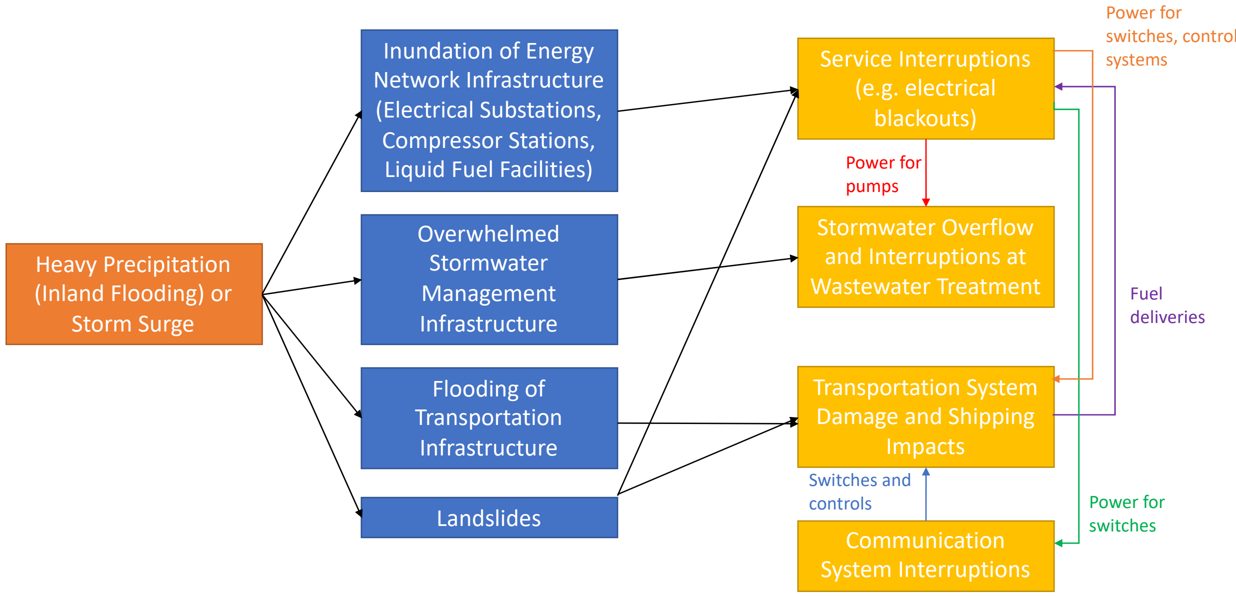


Figure 1: Illustrating Infrastructure Interdependencies. An initiating event (heavy precipitation or storm surge in this case) may directly affect multiple infrastructure systems as shown in the blue boxes. The impacts may cascade between systems, as shown in the yellow boxes and colored arrows.

Assessments of Pennsylvania's climate futures, including the previous installment of the Climate Impacts Assessment (Shortle, et al., 2015), the fourth National Climate Assessment (Zamuda et al., 2018) and Pennsylvania's recent Climate Action Plan generally indicate the following:

- Pennsylvania is likely to become warmer on average, and the likelihood of extended periods of extreme heat will also increase;
- On average, Pennsylvania is likely to become wetter. Precipitation, however, may become more volatile, with periods of intense rainfall being experienced more frequently. These periods of intense precipitation may be punctuated by periods of drought in the summer;
- The Southeastern corner of Pennsylvania may be vulnerable to sea level rise and more frequent coastal storm surge associated with an increased frequency in Atlantic hurricanes.

The aim of this report is to synthesize existing studies and information on how these climactic changes may affect the functioning of infrastructure systems in Pennsylvania, and to characterize possible changes in frequency and intensity of extreme weather events as Pennsylvania's climate changes. These discussions and analyses will be framed around the potential impacts of destructive weather events on infrastructure systems, as well as the readiness of Pennsylvania's infrastructure to continue to provide critical services in a future climate. We have several key findings:

- Flooding (related either to extreme precipitation or coastal storm surge in Southeastern Pennsylvania in particular) appears to have the most potential future impact on infrastructure systems in Pennsylvania. This makes Pennsylvania's infrastructure risk profile different than some surrounding states, and more concentrated on a single risk pathway. Generating detailed risk profiles for future flooding in Pennsylvania is difficult because a single state is below the resolution of most climate models. Available evidence suggests, however, that flood events in Pennsylvania will be tied closely to the remnants of Atlantic hurricanes. This suggests a link between the likelihood of extreme hurricanes and flooding in Pennsylvania.
- Drought and extreme heat may also pose challenges for infrastructure in Pennsylvania. Extreme heat in particular has been associated with public health challenges. The potential impacts posed by drought are less certain and are closely tied to the evolution of energy infrastructure in Pennsylvania. The ongoing market trend away from thermoelectric power plants requiring water for cooling will reduce the potential impacts of drought on energy infrastructure.
- Flood-related damage to infrastructure is likely to be very localized in nature. For example, flooding may cause local blackouts but by itself is unlikely to bring down the regional power grid. Localized flooding could, in some circumstances, disrupt rail and other transportation networks in ways that could have impacts on other infrastructure systems or broader economic activity.
- Large portions of multiple energy and transport infrastructures in Pennsylvania are potentially susceptible to direct damage from flooding. Particularly in the Southwestern portion of Pennsylvania, infrastructures face additional risk exposure from landslide potential associated with heavy precipitation events.
- Infrastructure planning to adapt to a changing climate occurs along multiple scales, with some decisions made locally and others made regionally or even nationally. Some of these planning processes have incorporated possible climate impacts while others have not.
- The impacts of extreme weather effects on infrastructure varies widely across Pennsylvania, with different counties having very different annual damages as well as a per-capita damage burden. Infrastructure readiness to cope with flooding and extreme heat events varies widely across Pennsylvania – some counties that appear to be the hardest hit historically are also among the poorest in the state.

2. Infrastructure Systems and Services in Pennsylvania

Existing physical infrastructure systems in Pennsylvania vary in geographic scale along with their function. Energy and transportation networks are very large scale systems that connect Pennsylvania to regional, national and international markets. The scope of some of Pennsylvania's larger infrastructure networks is shown in Figures 2 to 5. Water-related infrastructure, including municipal water supplies, stormwater systems and wastewater treatment plants are much more localized in nature.

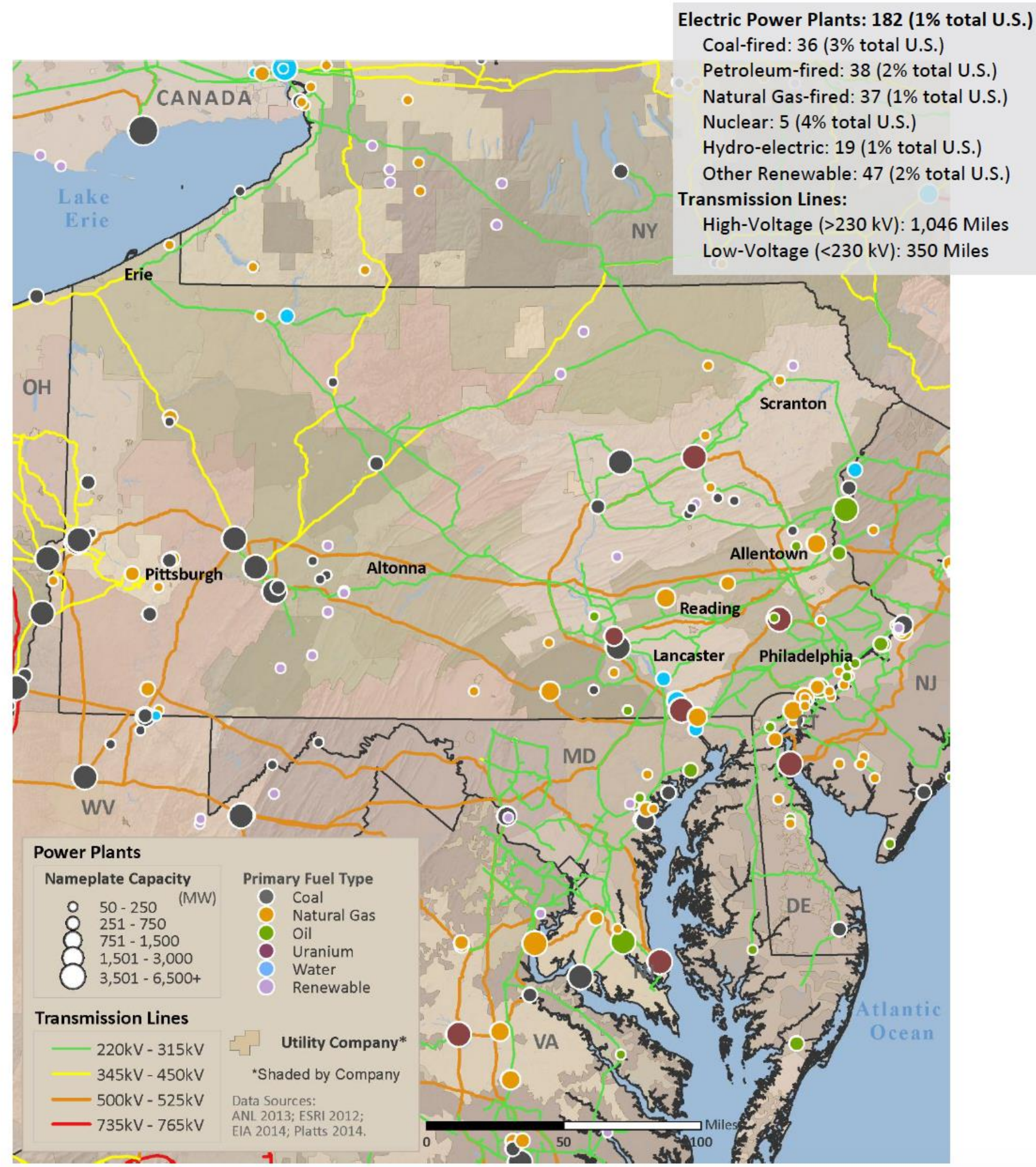


Figure 2: Electricity Infrastructure in Pennsylvania and the Region (EIA, 2015)

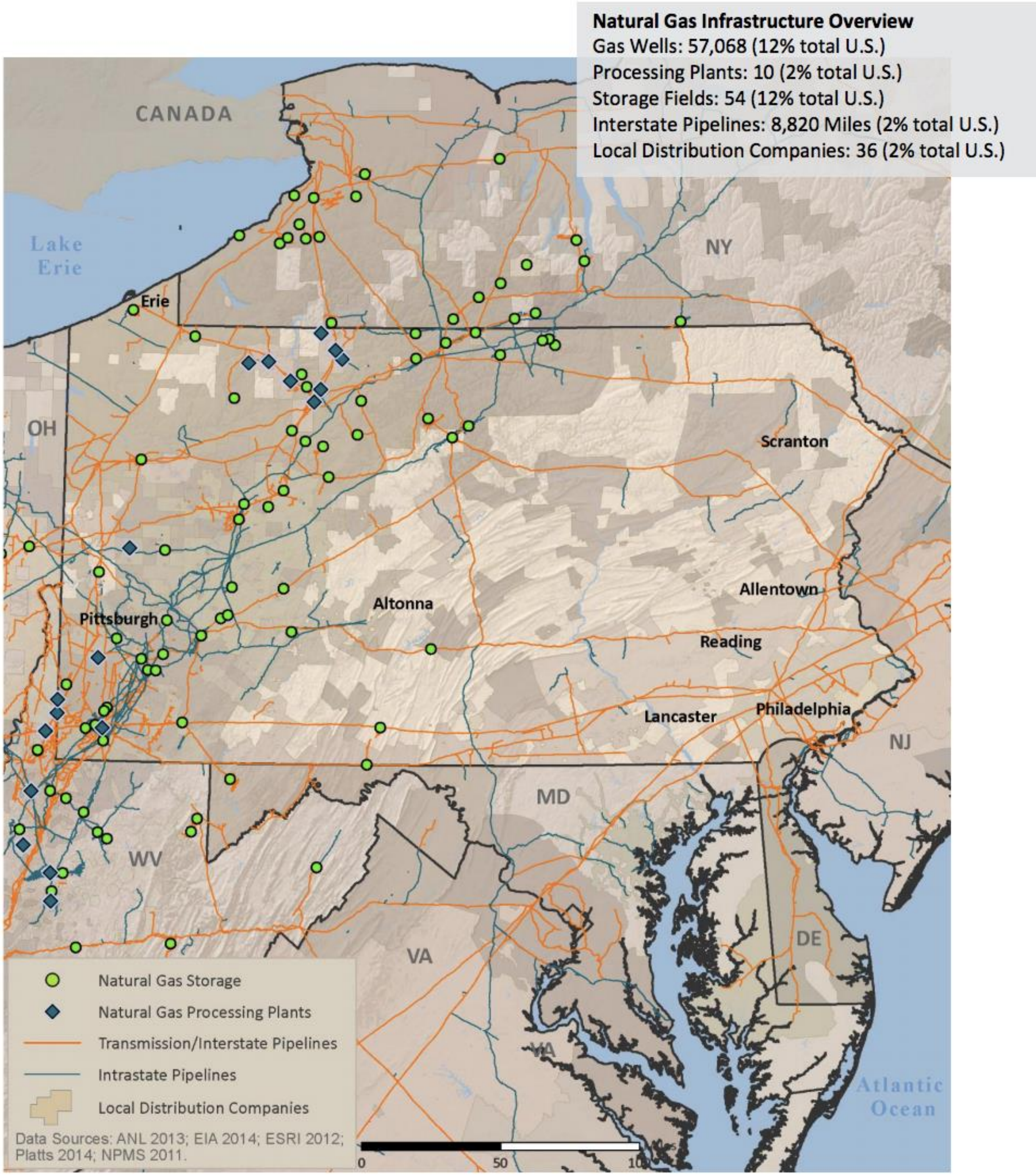


Figure 3: Natural Gas Transmission, Storage and Processing (EIA, 2015)

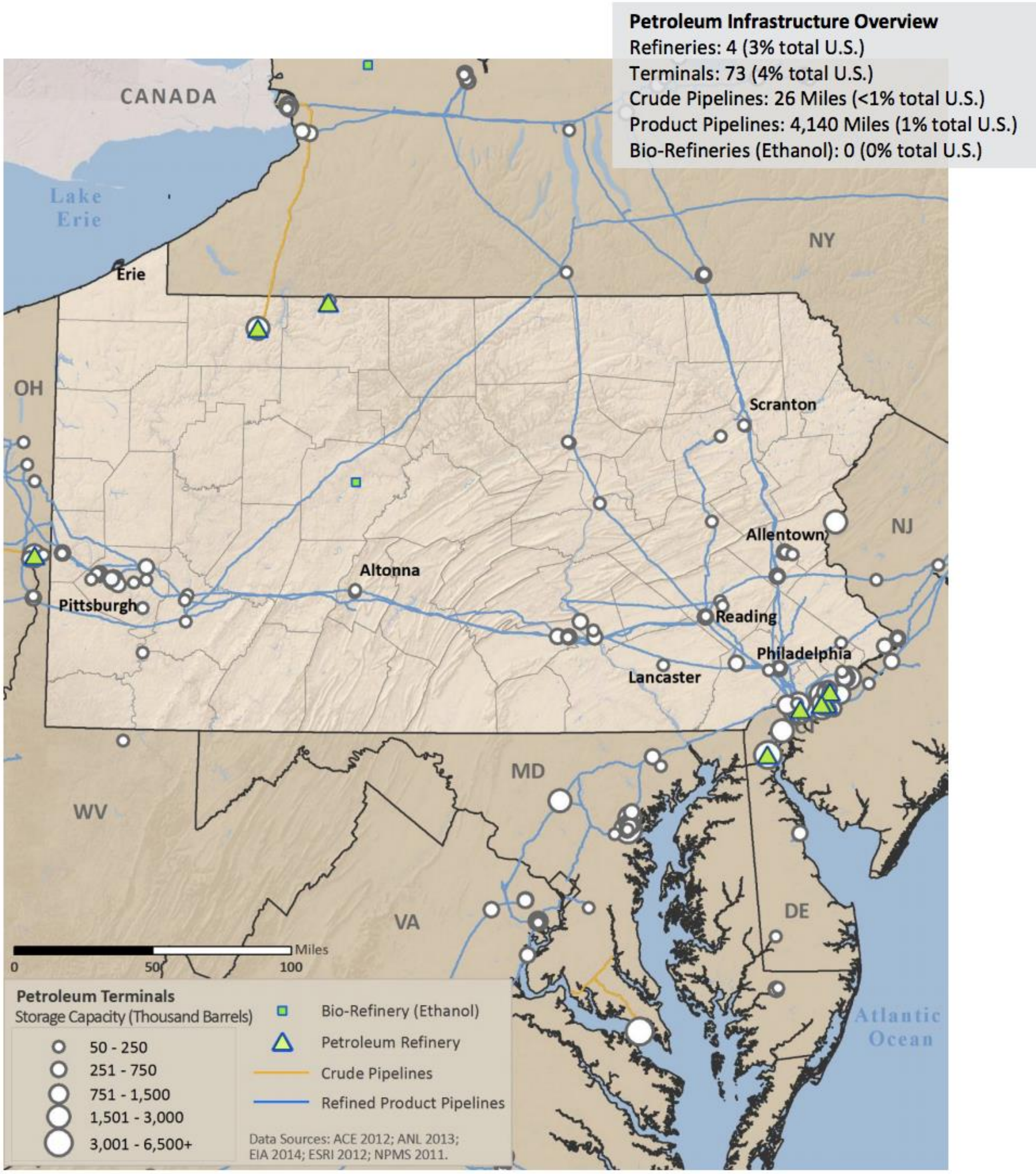


Figure 4: Transportation Fuels Infrastructure (EIA, 2015)

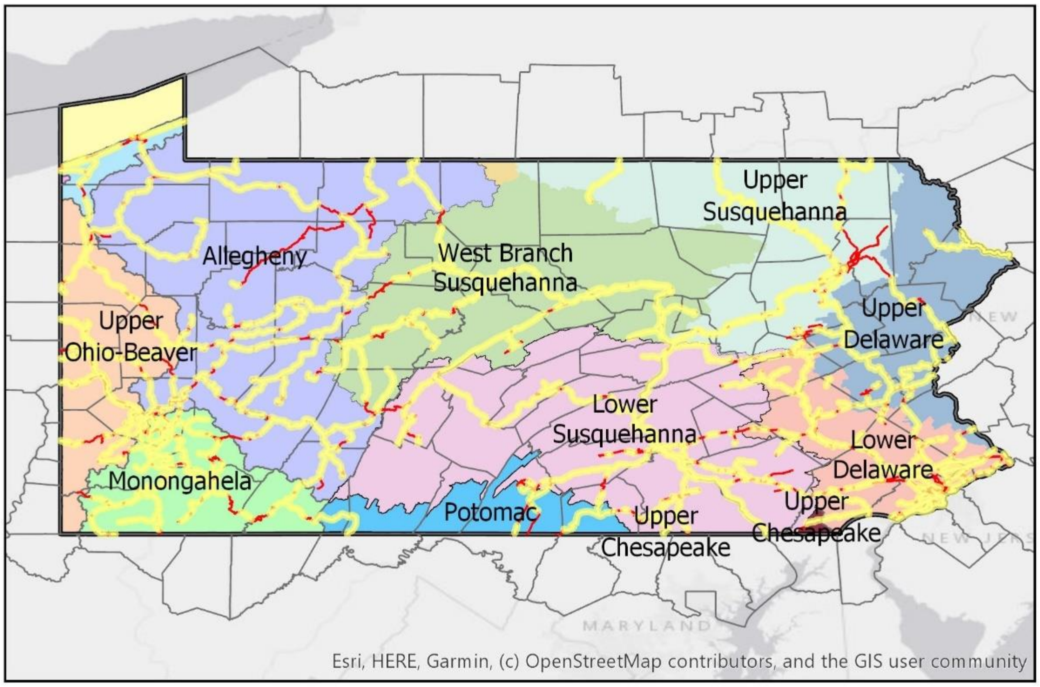


Figure 5: Rail Transport Network (Passenger and Freight) in Pennsylvania.

Pennsylvania's infrastructure has substantial capacity. The Commonwealth is one of the largest producers of electric power and natural gas in the U.S. and is the country's largest exporter of electricity to other states. Pennsylvania also has one of the most extensive rail transportation systems in the U.S. (including both passenger and freight rail). Regionally, Pennsylvania has historically been a major state for natural gas storage and petroleum refining, although the largest refinery in the Commonwealth permanently closed following a major fire.

Infrastructure systems in Pennsylvania exhibit several important interdependencies, some of which are summarized in Figure 1. Many infrastructure services, including fuels transportation and processing, the operation of water treatment and supply systems, and communications networks rely heavily on electricity. The power grid is also heavily dependent on communications networks for grid operators to issue dispatch instructions, and on fuel supply networks to ensure adequate power generation to meet demand. The nature of these interdependencies may change in the future depending on technological progress. The rapid switch to natural gas power generation, for example, increases the dependence of Pennsylvania's electricity system on natural gas supply systems, but decreases dependence on rail and barge transportation for coal and on water supplies for thermoelectric cooling (since natural gas power plants have lower water requirements than existing coal-fired or nuclear generating stations).

Also important is the fact that the role of local and state decision-makers in Pennsylvania can be limited in how infrastructure management decisions are made. Generally, the larger-scale an infrastructure system is, the less direct role that state or local decision-makers have in the planning and operation of those systems. Pennsylvania's high-voltage power grid, for example, is part of a larger regional system operated by PJM Interconnection, LLC. PJM is primarily regulated by the Federal Energy Regulatory Commission (FERC). Local distribution systems for electricity, which deliver power to end-use consumers from the high-voltage power grid, are regulated at the state or local level. Natural gas operates similarly, with the siting of interstate gas and petroleum pipelines being largely regulated by FERC and the state having more oversight of local distribution systems. The operation and management of water infrastructure, on the other hand, is much more localized. These differences in operational and decision-making scale are driven by a variety of factors, including scale economies for infrastructure networks and the need to move certain commodities over long distances.

3. Climate Impacts on Infrastructure Systems and Services in Pennsylvania

A changing climate has the potential to stress infrastructure systems and associated services in a variety of ways. Extreme weather events such as hurricanes, floods, extreme heat and drought can produce situations that damage infrastructure directly or reduce the capacity of infrastructure to meet service needs. Chronic stressors such as sea level rise or trends towards higher average temperatures represent ongoing hazards requiring some adaptation in planning and operations on the part of infrastructure managers.

The potential for climate-related stresses to negatively impact the reliable performance of large-scale infrastructure systems has been modeled in a number of different assessments (DOE, 2015; DOE, 2017; U.S. Zamuda et al., 2018). These assessments have been done at the regional or national level rather than at the state or local level in large part because of a lack of state-level downscaled estimates of climate-related extreme weather event risk. Shortle, et al. (2015) presents the only downscaled climate futures data for Pennsylvania specifically that we know of, and even these downscaled climate projections capture trends rather than the likelihood of specific extreme events.

3.1 Extreme Weather Impacts on Infrastructure

For the Northeastern region, existing studies are generally in agreement as to the potential impacts associated with extreme weather events. The major extreme weather events that appear to pose risks for infrastructure in Pennsylvania and the northeastern region include extreme heat, drought, hurricane force winds, and flooding from extreme precipitation or storm-related coastal surge.

- Periods of extreme heat will be associated with high demands for cooling and thus high demand for services from the electricity grid. Simultaneously, power grid operators often must reduce operable capacity on electric generation facilities and electric transmission lines during periods of extreme heat (Shortle, et al., 2015; Bartos, et al., 2016; Clarke, et al., 2018).
- Extended drought can impact the reliable operation of thermoelectric power plants through two mechanisms. Low water flow conditions may render cooling water for power plants unavailable, and the combination of high temperatures and low flow conditions may warm water beyond the point where it can be used for power plant cooling (Mackinick, et al., 2012).
- Intense hurricanes can produce winds capable of damaging power plants, electric transmission infrastructure, and fuel delivery infrastructure including fuel transportation (rail and roadways), natural gas compressor stations and pumping stations for crude oil and petroleum products. During both Hurricanes Irene and Superstorm Sandy, for example, electric and natural gas distribution systems were damaged or disrupted, and the storms affected production at Philadelphia-area refineries.
- Extreme precipitation events as well as coastal storm surge can inundate many different infrastructure facilities. Transportation infrastructure including roadways, bridges and rail corridors may be vulnerable to disruption from flooding, debris or landslides. The potential for damage associated with extreme rainfall is not limited to surface facilities or those in low-lying valleys or flood plains. Regionally, extreme rainfall and other weather events represent some of the largest sources of damage to pipelines that carry natural gas, crude oil or petroleum products, many of which are underground (DOE, 2015).

None of the studies that we reviewed highlighted wildfires or winter storms as extreme weather events expected to pose a major risk for infrastructure in Pennsylvania or the northeastern region. Pennsylvania is not considered to be a major risk area for wildfires, and future climate scenarios generally predict a decline in the number of extreme cold days as well as the demand for heating in Pennsylvania (Shortle, et al., 2015; DOE, 2015). As we will discuss further in Section 4, however, the social and economic costs of extreme winter weather have been rising in Pennsylvania.

3.2 The Nature of Infrastructure Vulnerability: Evidence from Irene and Sandy

Hurricane Irene, which struck the Eastern Seaboard in 2011 and Superstorm Sandy, which began as a coastal storm but moved inland over Pennsylvania, are relatively recent examples of extreme weather events that illustrate the kinds of vulnerabilities in Pennsylvania's infrastructure, particularly energy and transportation infrastructure. Since Pennsylvania's coastal exposure is much smaller than neighboring states (particularly New Jersey and New York), damage to Pennsylvania infrastructure was smaller than neighboring states, and the duration of service interruptions appears to have been shorter as well. Figure 6, from DOE (2013), illustrates Pennsylvania's infrastructure exposure for both storms.

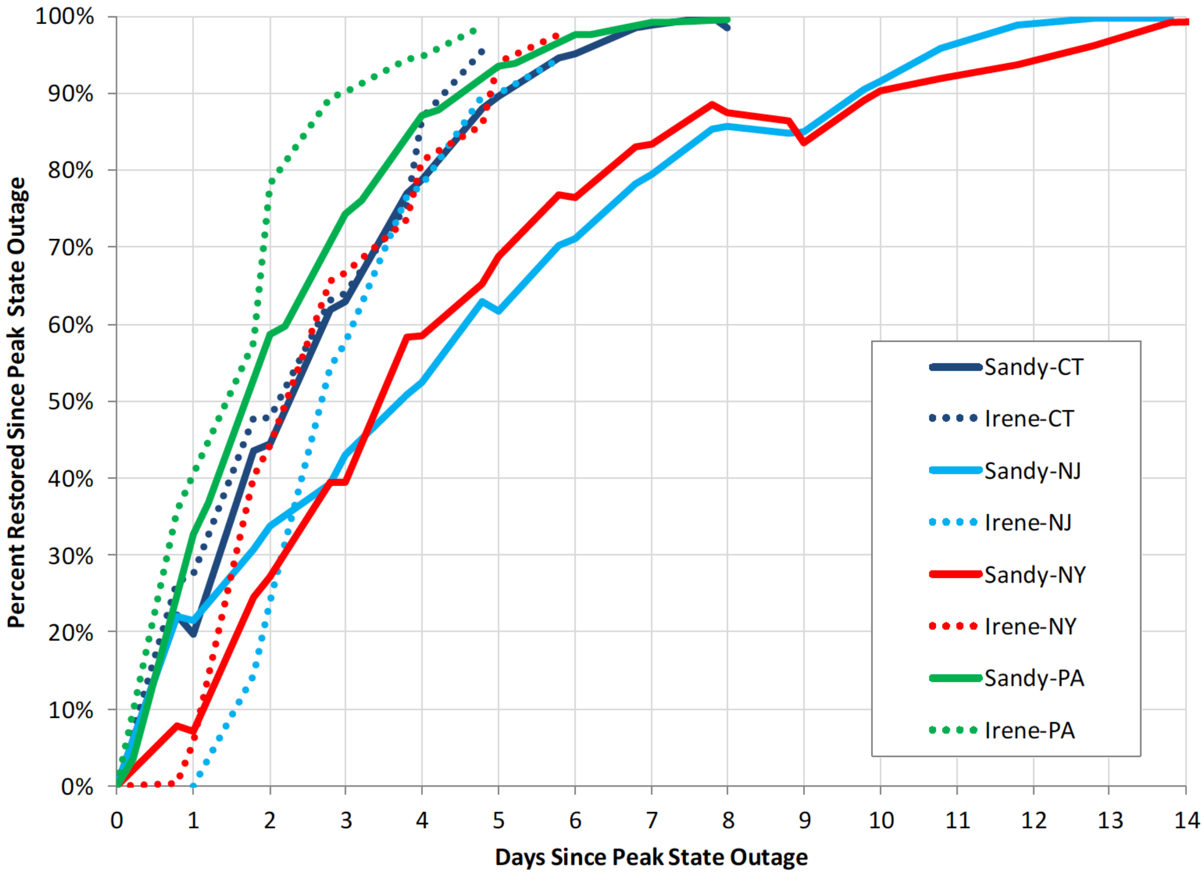


Figure 6: Power Outage Duration for Irene and Sandy (DOE, 2013).

Power outages during Irene affected around 700,000 people in Pennsylvania, while blackouts during Sandy affected around 1.2 million people in Pennsylvania. Sandy's impact in particular was large because of the particular path that the storm took, but outages in New Jersey and New York were 1.5 to 2 times more prevalent than those in Pennsylvania. Figure 6 shows that restoration happened more quickly in Pennsylvania than in other states in both Sandy and Irene, particularly in comparison to New Jersey and New York. Electric service in Pennsylvania was generally fully restored within four to five days following Irene and eight days following Sandy. In New Jersey and New York, however, service was not restored for two weeks or longer.

Table 1: Electric Power System Damage from Irene and Sandy in Pennsylvania. Adapted from DOE (2013)

	Damage Locations		Substations		Transformers		Transmission Lines		Sections of Wire		Poles	
	Irene	Sandy	Irene	Sandy	Irene	Sandy	Irene	Sandy	Irene	Sandy	Irene	Sandy
Met Ed	6,889	9,500			130	304	25	41	18 mi	53 mi	143	731
PECO		13,000			278	390			90 mi	141 mi	316	750
Penelec	1,483	1,800			10	88		42	3 mi	11 mi	30	80
PPL						601	18 mi			~100 mi	900	619
UGI Utilities	617	382							1,043		39	
West Penn Power		1,500				120		31		19 mi		65

Table 1, from DOE (2013) illustrates the nature of the damage to the electrical grid during Irene and Sandy. This data is based on reports filed with the Pennsylvania PUC and may not be complete. In particular, there is no data reported for substations in Pennsylvania (many of which help to regulate the local distribution of electricity). Sandy was generally a more damaging storm than Irene in most areas of Pennsylvania.

The information in Table 1 is useful in understanding the nature of disruptions to the power grid during extreme storm events. The majority of the damage during these events, which came primarily through a combination of high winds and flooding (including coastal surge in portions of Southeastern Pennsylvania), happened on the local distribution system and not on the high-voltage bulk power system. Since outages on the power grid during these storms were much more common in areas that saw high equipment damage (DOE, 2013), it can be inferred that those customers losing power in each of the two storms suffered blackouts because of storm-induced equipment damage on the local distribution systems. While outages were widespread in Pennsylvania, particularly during Sandy, they appear to have been caused by a large number of correlated failures on components of local distribution systems, as opposed to blackouts originating from the high voltage power grid. While there was damage sustained on some high-voltage electric transmission infrastructure and at some power plants in the region (particularly in New Jersey and New York), it does not appear that Pennsylvania suffered any kind of large-scale cascading failure of the bulk power grid. No direct storm-related damage on Pennsylvania power plants is available from either storm, but Pennsylvania's nuclear power plants in the eastern half of the Commonwealth continued to operate during the storms, although at reduced levels.

The loss of electricity also caused the shutdown of a number of water treatment facilities, principally in New York, New Jersey and the Washington, D.C. area (Climate Central, 2013). The loss of power at water treatment facilities led to the release of large amounts of untreated sewage into regional waterways. Pennsylvania also experienced some releases from affected water treatment plants, but at levels substantially lower than in New York or New Jersey. While power failures at water treatment plants were responsible for many of the sewage release incidents, it is worth noting that overflow due to heavy rainfall (a more direct event of extreme precipitation events) appears to have been responsible for the largest release incidents.

Flooding and coastal surge from both storms also affected transportation and fuel delivery infrastructure in Pennsylvania. Refineries in the Philadelphia area operated at reduced capacity during the storms and for several days afterwards, in the face of flooding conditions and some loss of electrical power. Refineries in New Jersey, also located in coastal areas, shut down entirely for as long as four months. Several petroleum product pipelines that carry gasoline and other fuels into Pennsylvania were also affected by flooding and loss of pumping power associated with Irene and Sandy. These product pipelines, particularly the Buckeye and Colonial pipelines, disrupted gasoline supplies to portions of Pennsylvania. (Power outages also affected the ability of retail gasoline stations to distribute fuel.)

Irene and Sandy carry some important lessons on the nature of infrastructure interruptions during extreme weather events, and appropriate responses to reduce vulnerability.

First, the regional bulk power transmission grid in Pennsylvania appears to be less vulnerable to storm damage and flooding, and local distribution systems appear to be more vulnerable. Electric power infrastructure is thus much more locally vulnerable to the kinds of events likely to become more common in Pennsylvania than it is regionally vulnerable. While the process of planning the bulk power grid has generally not taken climate change into account in any kind of anticipatory way, particularly related to failure modes for equipment on the grid (Murphy, et al., 2018), there are responses that can happen on the local level to address more immediate vulnerabilities.

During Sandy in particular, several types of distributed energy systems were able to continue providing energy services in the face of disruptions on local electricity and natural gas distribution systems (ACEEE, 2012; Govindarajan and Blumsack, 2016). Distributed energy systems, which include renewable solar as well as efficient combined heat and power for commercial buildings and campuses, have been mentioned in Pennsylvania's Climate Action Plan as a mechanism to reduce greenhouse gas emissions from the electricity sector. They also have a role to play in the "survivability" of energy infrastructure – the ability of systems to continue providing services in the face of external disruptions (Talukdar, et al., 2003). While distributed energy and micro-grids are increasingly encouraged in Pennsylvania, there are no existing customer-side commercial standards for resilience on the electric distribution grid. One option that could be encouraged among commercial customers and campuses is certification in the PEER program (Performance Excellence in Electricity Renewal), which operates in a manner similar to the LEED building standards established by the U.S. Green Building Council.

The second lesson related to infrastructure vulnerability in Pennsylvania is that the interconnected nature of infrastructure systems in the U.S. can, in some cases, leave Pennsylvanians vulnerable to climate impacts that occur well outside of the state's borders. When Irene and Sandy interrupted the petroleum product refining and delivery infrastructure, the result was price increases of 10% or more for gasoline and other petroleum products that persisted months in the case of both storms. These price increases persisted because of damage to refining and shipping infrastructure that limited the amount of petroleum products that could have been produced in the region or imported from other regions. Particularly in the case of petroleum transportation fuels, which must either be produced in the region from crude oil shipped from elsewhere or imported from outside the region.

3.3 Stormwater System Readiness

Climate assessments for the U.S. northeast have generally projected an increase in the frequency and severity of intense precipitation episodes. This has the potential to overwhelm combined stormwater and wastewater systems in urban areas, leading to combined outflows that are harmful to water quality.

Planning decisions for stormwater infrastructure (or combined stormwater/wastewater infrastructure) happen at multiple levels and are based on specification and best management practices document from multiple entities (including the Pennsylvania DEP and the U.S. Department of Transportation). Individual municipalities also make their own system decisions, and some larger cities in Pennsylvania (including Harrisburg, Philadelphia and Pittsburgh) have begun investing in stormwater management infrastructure designed to reduce the amount of rainfall that eventually goes into combined systems.

Lopez-Cantu and Samaras (2018) recently performed an assessment of the precipitation frequency assumptions used in developing stormwater management plans across the U.S. These assumptions are typically based on historical data, which may not be a good guide for future decisions in the face of changing precipitation patterns. They compared when each state had updated its best management practices or other guidelines for stormwater system design with updates to published (historical) precipitation patterns, and compared those historical patterns to modeled future precipitation extremes under high and low emissions scenarios. They concluded that while Pennsylvania's stormwater best management practices are relatively up to date (in the sense of using the latest available precipitation data), the Commonwealth should continue incorporating anticipatory projections of extreme precipitation as it updates its best management practices for stormwater system engineering.

3.4 Technological Change and Energy Infrastructure Risk

This report has discussed how extreme storms and flooding can affect infrastructure. Existing assessments have also pointed towards drought and extreme heat as potential infrastructure stressors, particularly for electric power systems. Both drought and extended periods of high temperatures can lead to situations where electricity demand for cooling (and water pumping) is high, but supplies are restricted. Power grid operators generally need to reduce the operable capacity of electric transmission lines and power plants during extreme heat periods. Drought can also serve to reduce available electricity supplies by restricting the availability and use of water for thermoelectric cooling. While drought has not caused substantial power interruptions in Pennsylvania, it has affected individual power plants.

The plants that are most vulnerable to drought are those that employ once-through cooling cycles and thus do not recycle or re-use cooling water. In Pennsylvania, these are primarily older steam turbines that use coal or nuclear fuel. Many of these power plants, particularly older coal-fired plants, have retired in recent years (or will retire soon) and are being replaced with a mix of natural gas and renewables. This changes the technology mix in the grid, but also the geography and water-intensity of power generation as shown in Figure 7.

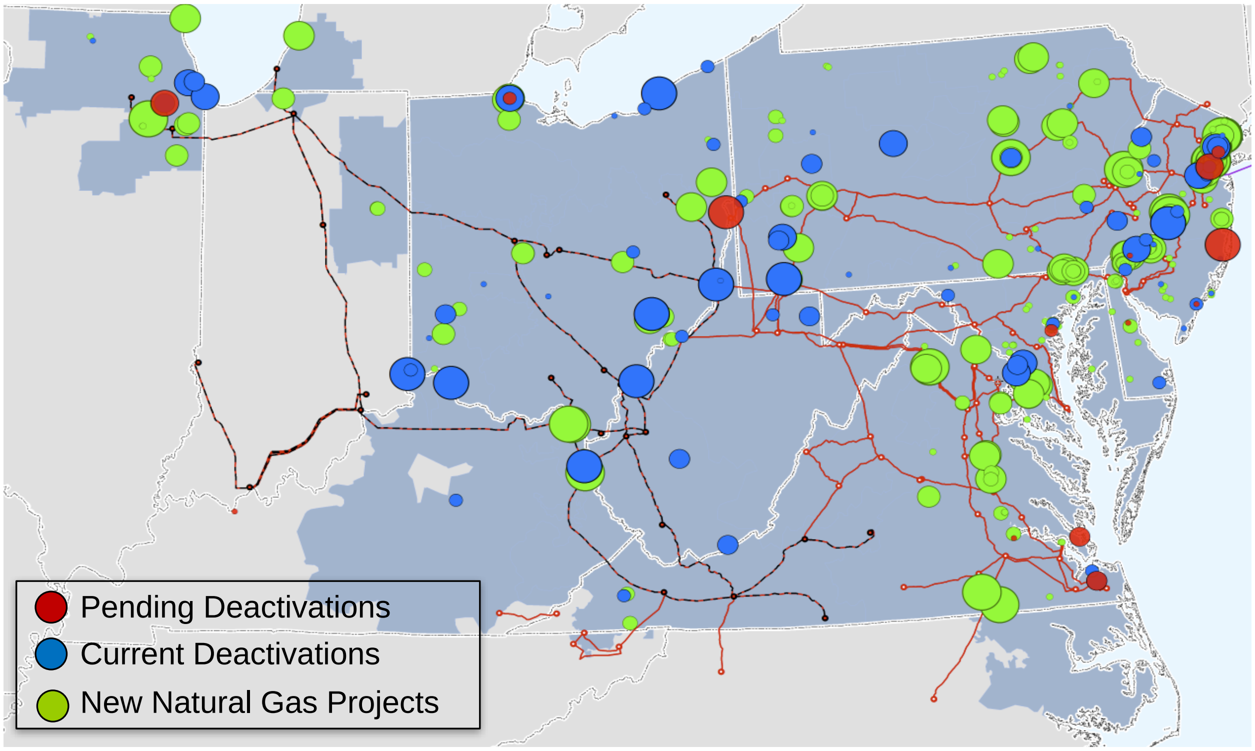


Figure 7: Changes in the Technology Mix in the PJM Power Grid, 2017. Source: PJM.

Figure 7 shows how one locus of power generation activity, in Western Pennsylvania and the Ohio River Valley, is shifting towards the eastern portion of the PJM territory. The large number of current deactivations in the PJM service territory is occurring in areas along major waterways. These were formerly advantageous areas to build power plants because of proximity to both cooling water and fuel transportation infrastructure (barge and rail). New natural gas projects are emerging that are tending to be closer to both major demand centers in PJM as well as major natural gas pipeline infrastructure.

Assuming that this trend continues and the use of renewables and natural gas in the regional power grid continues to grow, one implication of this technology transition is to increasingly decouple the power grid from water availability. This may mean less vulnerability of electricity infrastructure to drought or extreme heat conditions that would otherwise affect the availability of cooling water. It is important to note, however, that this technology transition may reduce one infrastructure interdependency (water and the power grid) but increase others. In particular, the interdependence of the power grid and the natural gas transmission system is likely to increase.

The example of changing technology for electric power generation illustrates the distinction between nearer-term and longer-term vulnerabilities. Thermoelectric plants requiring high availability of cooling water are likely to continue to operate in some capacity for a number of years – thus in the near term (over the next one to two decades), the potential for drought will continue to serve as a source of vulnerability for electrical infrastructure. Over the longer term, the most relevant interdependencies and climate-related interactions may change.

4. Flooding Dominates Damage from Extreme Weather Events

Data on the infrastructure impacts of extreme weather are not uniformly or evenly available. Where data are available, they generally reflect incidents of service interruptions on large-scale systems such as power grids or pipelines. The need for better data and analysis on infrastructure interruptions has been raised in the literature (Fisher, et al., 2012; Apt et al., 2018; Murphy et al., 2018). This is especially the case for impacts on local infrastructure, which are not subject to federal incident reporting requirements.

To get some sense of the importance of flooding in damage to local infrastructure in particular, we have examined data on weather-related property damage and social impacts at the county level in Pennsylvania. While these data sets focus on private property damage, fatalities and injuries, we can use them to get a sense of how the risk exposure to different extreme weather events varies across Pennsylvania. Because of the nature of many kinds of extreme weather events, damage to property is likely spatially correlated with damage to local infrastructure. Weather-related fatalities can be viewed as a proxy for infrastructure readiness to handle extreme events. We are particularly interested in looking at the spatial and temporal variability of the costliest events for the state – floods – and how location, population, and income interact with these events. Specifically, we want to know which places and people have been and are likely going to be the most vulnerable to extreme events. This information can help to inform future infrastructure investments to adapt to a changing climate in Pennsylvania.

4.1 Data

The data used in this section of the report come from several sources. The main data source is NOAA's Storm Events Database (NOAA-NCEI, 2019b). This database, which is maintained by the National Weather Service, tracks severe weather events across the U.S. at the county level from 1950 through the present. The database keeps track of numerous variables associated with each event including scale (location) and type of event, injuries and fatalities, and property and crop damages. While the information in the database is collected and aggregated across many different sources, the most common sources of information on damages and loss of life are from emergency service agencies and planning authorities in the counties impacted by the event. Given that the database has expanded over time increasing the number of events that it tracks, it is only possible to use the full database starting in 1996.[2]

[2] While the database tracks several events going back into the 1950's, it only started tracking loss of life and property damages for floods in 1996. Given the impact that floods have had on the state of Pennsylvania, we only use these data starting in 1996.

Table 2: Impacts of Weather Related Events in Pennsylvania, 1996-2018

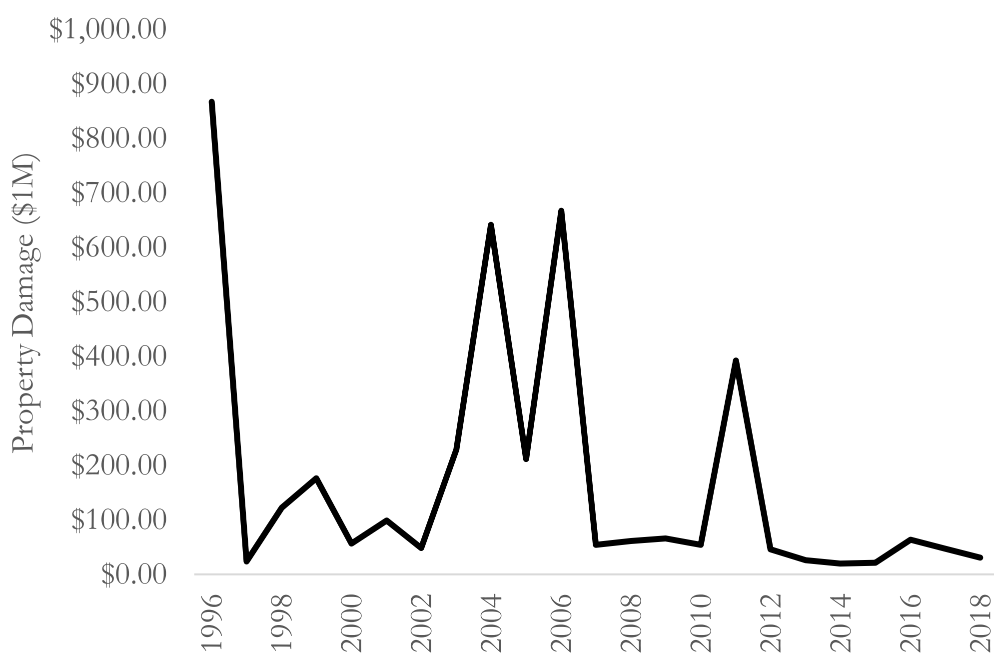
Year	Property Damage	Fatalities (1)	Fatalities (2)	Injuries (1)	Injuries (2)
1996	$867.17	37	0.30	52	0.43
1997	$23.94	49	0.40	84	0.69
1998	$122.00	20	0.16	264	2.16
1999	$176.72	101	0.82	358	2.92
2000	$56.88	24	0.20	17	0.14
2001	$99.08	31	0.25	32	0.25
2002	$48.86	49	0.40	141	1.14
2003	$229.36	21	0.17	32	0.26
2004	$641.32	20	0.16	233	1.88
2005	$212.08	35	0.28	73	0.59
2006	$667.72	48	0.38	62	0.50
2007	$54.59	11	0.09	53	0.42
2008	$60.97	45	0.36	139	1.10
2009	$66.07	8	0.06	110	0.87
2010	$54.32	33	0.26	23	0.18
2011	$392.02	68	0.53	110	0.86
2012	$46.16	40	0.31	107	0.84
2013	$26.56	15	0.12	73	0.57
2014	$19.84	16	0.13	109	0.85
2015	$21.60	23	0.18	135	1.06
2016	$63.08	34	0.27	90	0.70
2017	$46.66	8	0.06	12	0.09
2018	$30.65	5	0.04	16	0.12

Notes: This table shows annual weather-related property damages, fatalities, and injuries for the state of Pennsylvania from 1996-2018. All property damages are listed in millions of $2018. For fatalities and injuries, column (1) lists the total for each year from the NOAA fatalities databse, and column (2) lists the total in each year per 100K based on state population in that year.

In addition to NOAA's storm data, we also collected income and population data from the Bureau of Economic Analysis and the U.S. Census Bureau, housing transactions data from Zillow, and spatial data on flood risk from FEMA. The BEA/Census data provide yearly estimates of population and income per capita for each county in Pennsylvania, which allows us to look at the socioeconomic impacts of extreme weather events – i.e., how each person in a county shares in the damages from flood events.[3] The Zillow and FEMA data allow us to get a spatially explicit look at how much housing infrastructure in the state is located in high-risk areas, whether this varies across counties, and how this at-risk infrastructure correlates with past flood events.

4.2 Analysis

We begin by looking at trends in property damages, fatalities, and injuries from all weather-related events in the state from 1996-2018 (Table 2 and Figure 8). For property damages, all values are summed across counties for each year and presented in $2018. For fatalities and injuries, values are summed across counties for each year in column (1) and normalized per 100K people in column (2) based on yearly county populations. From these results, we see (1) that damages and fatalities have trended slightly downward over time, although this trend is punctuated by periods of abnormally high impact[4] and (2) that property damages, and to some extent fatalities, have been driven by substantial jumps in specific years. For fatalities, the association over time appears to be quite tight and, as we will see later, is mostly driven by a fall in heat-related deaths, which is offset somewhat by an upward trend in winter-weather-related fatalities. For property damages, the association is not as tight, but still displays a downward trend, and the results, like fatalities, are driven to a large extent by losses from a single event type, flooding.



[3] To make damage estimates and income comparable over time, we use the Bureau of Labor statistics CPI-U value for the Northeast U.S. to put place are monetary values into $2018.

[4] A plot for injuries (not shown) shows a similar downward trend.

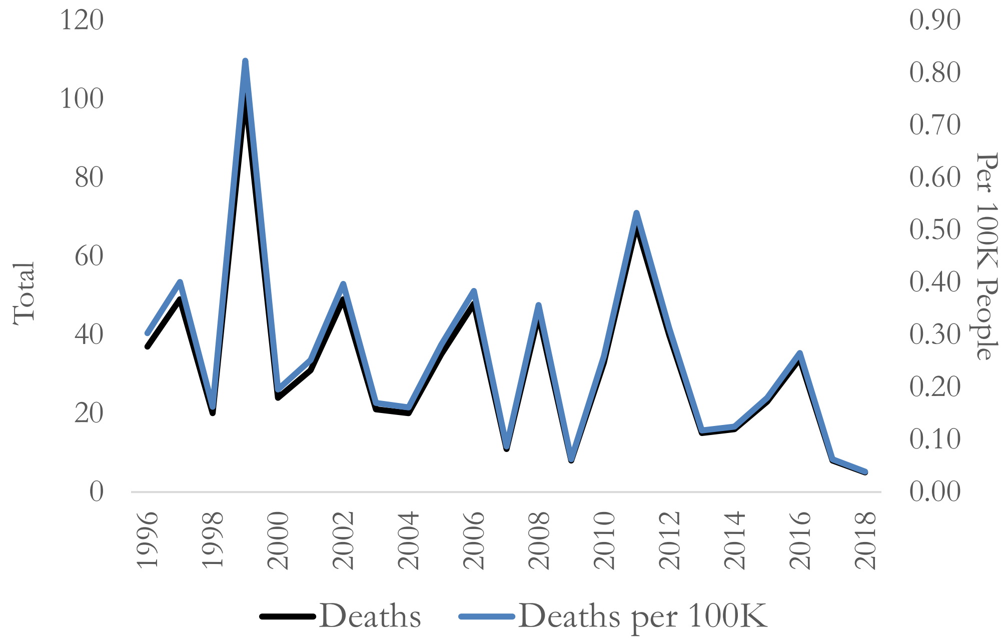


Figure 8: Weather Related Property Damage and Fatalities, 1996-2018
Notes: The top figure shows trends in annual property damages from all weather-related events for the state of Pennsylvania. The data are shown in millions of $2018. The bottom panel shows trends in annual fatalities from weather-related events. Injuries (not shown; displayed in Table 1) show similar trends to fatalities. All data comes from NOAA's storm events database.

In Table 3, we present totals, in column (1), and shares, in column (2), across time, for property damages, fatalities, and injuries for 20 different weather events. While the NOAA storm-events database categorizes 48 event types, some of these either do not exist in Pennsylvania or produce no losses so we exclude them from our analysis. In addition, to create our winter weather category we combine eight sub-categories (Winter Storm, Blizzard, Heavy Snow, Ice Storm, Sleet, Lake-Effects Snow, Frost/Freeze, and Freezing Fog) and produce a single event "Winter Weather". This process leaves us with the 20 categories in Table 3.

Several important things stand out from Table 3. First, close to 80% of the over $4 billion in property damages that occurred because of weather events during our study period were the result of flooding events with over 50% resulting from flash floods, which is not particularly surprising given the topography of much of the state. Second, close to 56% of all fatalities were the result of excessive heat events. While it is not possible to get a perfect count of all weather-related deaths, this fact – that heat has led to the largest share of deaths – is consistent with the results in Figure 9. In that figure, Drought, which includes high-heat events, led to the second most deaths behind hurricanes. Given that Pennsylvania does not suffer from hurricanes on a regular basis and has a limited coastal population, it stands to reason that the state would be more likely to suffer fatalities from heat. Third, combining flooding, heat, and winter weather events together accounts for over 83% of all fatalities. And finally, while injuries are somewhat distributed across several events the majority resulted from winter weather events. While the NOAA data does not tell how injuries occurred (they do for fatalities), it is likely that most of these are the result of traffic accidents. The fact that winter weather is the largest share for injuries, but not for fatalities is probably the result of increased automobile and highway safety.

Table 3: Impacts by Weather Event Type for Pennsylvania

	Property Damage		Fatalities		Injuries	
	(1)	(2)	(1)	(2)	(1)	(2)
Event Type						
Cold	$2.05	0.001	33	0.045	1	0.000
Debris Flow	$0.08	0.000	0	0.000	0	0.000
Dense Fog	$0.00	0.000	0	0.000	13	0.006
Drought	$0.00	0.000	0	0.000	0	0.000
Flood	$1,025.05	0.255	31	0.042	107	0.046
Flood - Coastal	$0.52	0.000	0	0.000	1	0.000
Flood - Flash	$2,155.65	0.535	58	0.078	52	0.022
Flood - Lakeshore	$0.01	0.000	0	0.000	0	0.000
Hail	$6.46	0.002	0	0.000	0	0.000
Heat	$0.04	0.000	418	0.564	449	0.193
Heavy Rain	$0.00	0.000	2	0.003	4	0.002
Landslide	$0.02	0.000	0	0.000	0	0.000
Lightning	$20.23	0.005	21	0.028	214	0.092
Tropical Storm	$4.06	0.001	1	0.001	197	0.085
Wildfire	$1.72	0.000	1	0.001	0	0.000
Wind - High	$141.32	0.035	36	0.049	9	0.004
Wind - Marine High	$0.00	0.000	0	0.000	57	0.025
Wind - Thunderstorm	$236.60	0.059	23	0.031	0	0.000
Wind - Tornado	$212.75	0.053	6	0.008	248	0.107
Winter Weather	$221.09	0.055	111	0.150	972	0.418
Totals	$4,027.64		741		2,324	

Notes: This table shows weather-related property damages, fatalities, and injuries, by event type, for Pennsylvania during the period 1996-2018. All property damages are listed in millions of $2018. For fatalities and injuries, column one lists the totals by event type, and the second column gives the share associated with each event type. All results are based on data from NOAA's storm events database for the state of Pennsylvania 1996-2018.

To provide some comparison and context for the results for Pennsylvania (Table 3), in Table 4 we provide a similar analysis for the state of Ohio. While Ohio and Pennsylvania are similar in size and have a lot of economic parallels, their profiles for weather-related damages, fatalities, and injuries are different. Comparing at columns (1) and (2) in Tables 3 and 4, we observe that total property damages in Ohio are larger than in Pennsylvania – during the period from 1996 through 2018 the state of Ohio experienced over $3 billion more in damages than Pennsylvania – and that much of this difference comes from larger losses associated with wind and summer-storm related events such as hail. Specifically, we find that wind and hail together accounted for 46% of the losses in Ohio during our study period. Flooding, on the other hand, accounts for 31% of losses in Ohio (whereas flooding accounts for 79% of losses in Pennsylvania). This comparison exercise makes clear that the needs of Pennsylvania in terms of planning for damage associated with extreme weather events may be very different than surrounding states.

Table 4: Impacts by Weather Event Type for Ohio

	Property Damage		Fatalities		Injuries	
	(1)	(2)	(1)	(2)	(1)	(2)
Event Type						
Cold	$26.53	0.004	10	0.048	0	0.000
Dense Fog	$0.80	0.000	6	0.029	42	0.039
Drought	$0.00	0.000	0	0.000	0	0.000
Flood	$438.25	0.061	24	0.116	9	0.008
Flood - Coastal	$9.06	0.001	0	0.000	0	0.000
Flood - Flash	$1,823.56	0.256	37	0.179	10	0.009
Hail	$1,151.33	0.162	0	0.000	4	0.004
Heat	$0.02	0.000	16	0.077	0	0.000
Heavy Rain	$0.87	0.000	2	0.010	0	0.000
Landslide	$0.00	0.000	0	0.000	0	0.000
Lightning	$18.85	0.003	24	0.116	120	0.111
Waterspout	$0.01	0.000	0	0.000	0	0.000
Wind - High	$1,045.37	0.147	18	0.087	83	0.076
Wind - Thunderstorm	$340.41	0.048	28	0.135	206	0.190
Wind - Tornado	$741.58	0.104	22	0.106	320	0.295
Winter Weather	$1,530.89	0.215	20	0.097	291	0.268
Total	$7,127.54		207		1,085	

Notes: This table shows weather-related property damages, fatalities, and injuries, by event type, for Ohio for the period 1996-2018. All property damages are listed in millions of $2018. For fatalities and injuries, column one lists the totals by event type, and the second column gives the share associated with each event type. All results are based on data from NOAA's storm events database for the state of Ohio 1996-2018.

Given the previous results, we are now going to examine more closely the biggest contributors to fatalities – flooding, heat, and winter weather – and property damages – flooding. We begin with fatalities. In Figure 9, we plot the time series for flooding, heat, and winter weather deaths, and in Table 5 we show the age and gender distributions for each of these events. The left axis in Figure 9 is for heat and the right axis is for flooding and winter weather. From these results, we see that both heat and flooding deaths have declined over time and winter weather deaths have increased. We also see that heat-related deaths afflict older populations more than the other two categories, and all three impact males more than females. The downward trend for heat is consistent with a longer-run decline at the national level, especially for older people, going back to the 1960s, which has been attributed to increased AC adoption (Barreca et al. 2016). While it is not possible to attribute a single cause to the shorter-run decline in Pennsylvania, the downward trend for heat, and the fact that the average age for those deaths is 68 (Table 5), suggests similar mechanisms may be at work. It also suggests areas where infrastructure investments may continue to help reduce heat-related deaths – i.e., investments that will allow more vulnerable populations to adapt to increasingly warmer temperatures over the coming decades, especially in urban areas. The rise in winter weather deaths, while troubling, is not surprising to the extent that this rise can be attributed to deaths related to motor vehicle accidents.[5] Given rising populations and vehicle miles traveled over time, it is likely that if we normalized by these data by miles and/or population the trend would either be less steep or decline. One interesting detail about the trend associated with winter weather, as it relates to climate change, is that that to the extent that a warmer climate decreases the severity of winter weather in the state it may lead to a decrease in winter-weather deaths, a fact that has been predicted in other research (Hsiang et al. 2017).

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[5] The NOAA fatalities data show that of the 111 winter weather deaths, 72% of them occurred in a motor vehicle.

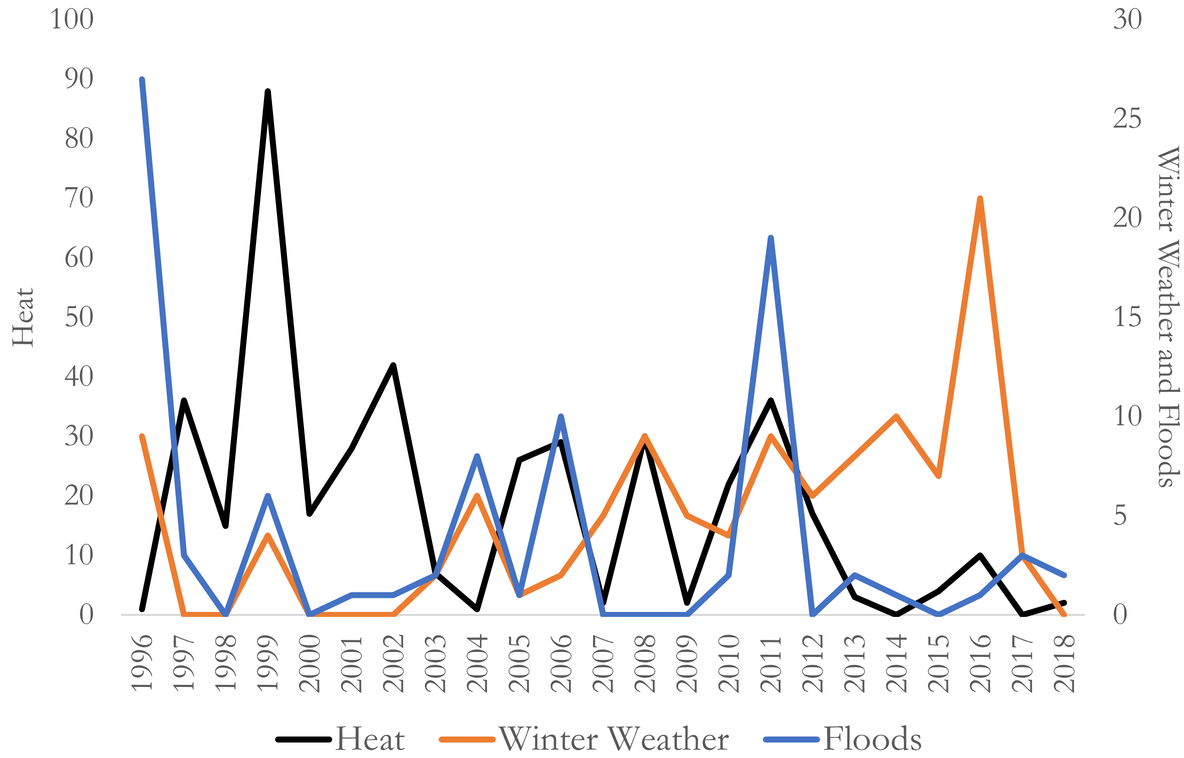

Figure 9: Total Weather Related Fatalities by Event Type, 1996-2018

Table 5: Age Distribution of Fatalities by Event Type, 1996-2018

	Fatalities Age Distribution by Event Type				Share Male
Event	Mean	Median	10th	90th	
Flood	45.52	45	15	76	0.65
Heat	68.97	72	49	88	0.60
Winter Weather	52.02	54	21.5	83	0.65

Notes: These data were produced by merging the NOAA storm events dataase with the NOAA fatalities database. All results are for weather events occurring from 1996-2018.

Turning to property damages, we focus on the spatial distribution – across counties – of flooding events.[6] We first look at the spatial distribution of total property damages. Figure 10 shows a map of the state with each county shaded based on the total property damages that occurred because of flooding from 1996-2018 with darker colors signifying larger losses. We present the map results using the natural log of losses given the power-law nature of the distribution. In Table 6, we show, in unlogged form, the top 20 counties, in terms of losses, and their associated metro areas. We observe that there is a high degree of spatial variation in losses across Pennsylvania. Losses are heavily concentrated in urban counties and in the Northeast part of the Pennsylvania. Losses are also heavily concentrated in the Susquehanna watershed. To provide some additional context for the association between property losses and economic outcomes, in Figure 11 we plot county-level losses (logged) against logged population (left sub figure) and logged real income per capita (right sub figure). In both cases, we see a positive association between population and income. This result is consistent with losses from flooding in the broader U.S. context – i.e., rising losses from flooding can, at least in part, be attributed to the rising population, income, and house values (Kousky, 2019).

[6] We do not look at time trends related to flooding, as we did with fatalities, as these trends and figures look very similar to those in the top part of Figure 8 given how large of a share of property damages come from flooding.

Table 6: Pennsylvania Counties with Highest Flood Damage ($ Million), 1996-2018

County	Metro	Total
Luzerne	Scranton--Wilkes-Barre	$373.26
Bucks	Philadelphia	$199.07
Wyoming	Scranton--Wilkes-Barre	$184.61
Jefferson		$167.27
Dauphin	Harrisburg-Carlisle	$165.78
Susquehanna		$158.58
Bradford	Sayre	$154.98
Montgomery	Philadelphia	$150.93
Lackawanna	Scranton--Wilkes-Barre	$136.02
Monroe	East Stroudsburg	$132.87
Wayne		$129.52
Clarion		$125.46
Allegheny	Pittsburgh	$116.55
Crawford	Meadville	$98.41
Venango	Oil City	$83.80
Pike		$75.27
Northampton	Allentown-Bethlehem	$73.73
Warren	Warren	$67.06
Beaver	Pittsburgh	$57.18
Berks	Reading	$48.51

Notes: This table lists the top 20 counties in terms of total property damages for flooding from 1996-2018. All property damages are listed in millions of $2018. The first column gives the county name, the second column lists the metro area associated with the county based on U.S. Census definitions, and the last column lists total property damages.

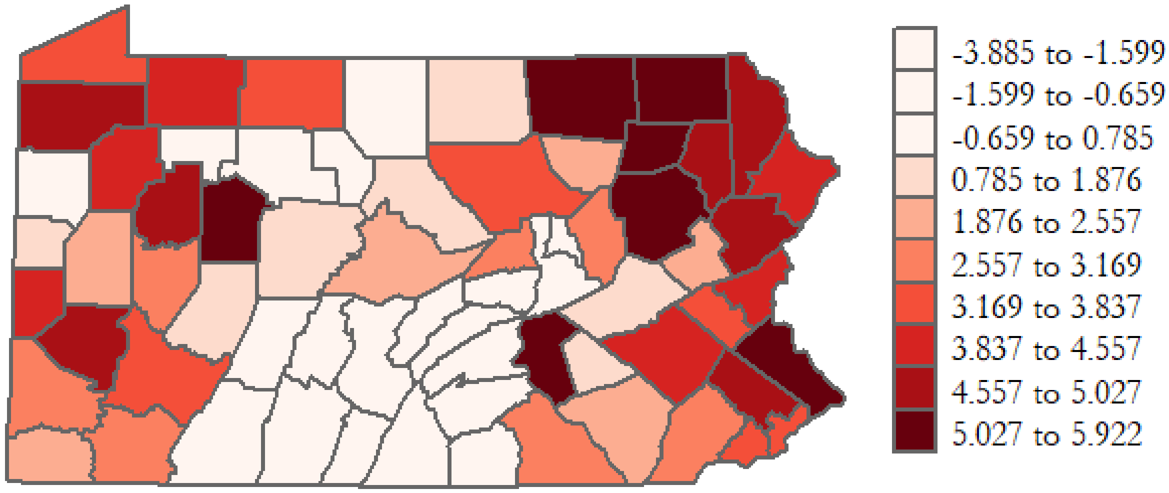

Figure 10: Total Property Damages from Flooding, 1996-2018

Notes: This figure shows the natural log of total property damages from flooding from 1996-2018 for each county in Pennsylvania. The legend shows deciles of the state-level distribution. All values are in millions of $2018.

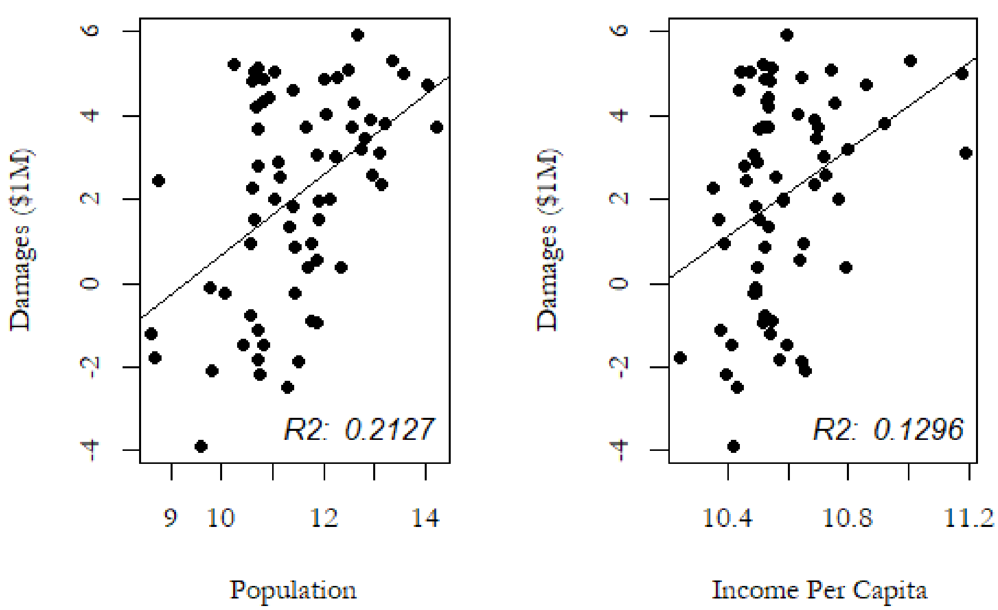

Figure 11: Damages vs. Population and Income Per Capita

Notes: This figure shows the natural log of total property damages from flooding from 1996-2018 for each county in Pennsylvania vs. the natural log of population (left figure) and vs. the natural log of per capital income (right figure). All damage values are in millions of $2018.

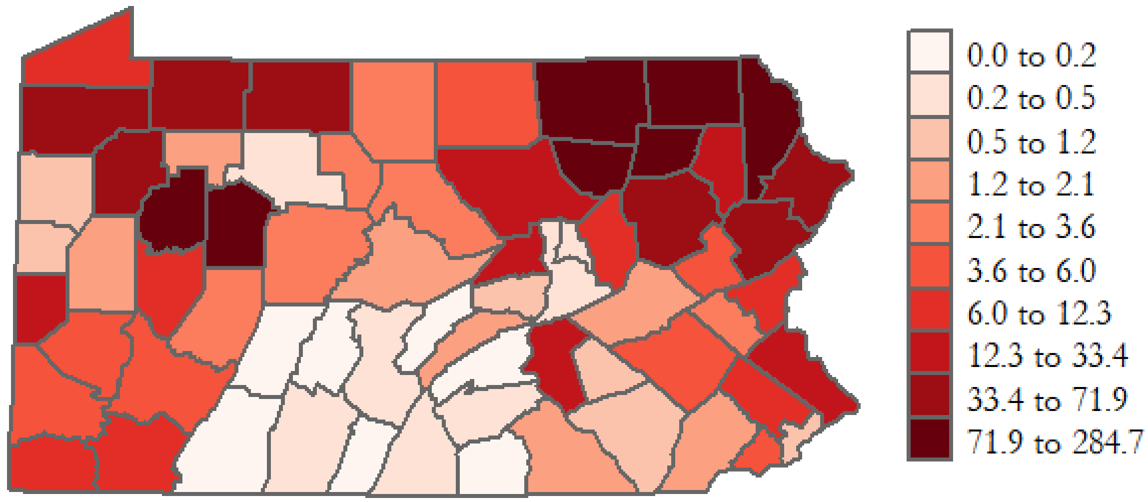

Figure 12: Total Annual Flooding Losses, 1996-2018

Notes: This figure shows yearly per capita property damages from flooding averaged over the period 1996-2018 for each county in Pennsylvania. The legend shows deciles of the state-level distribution. All values are in millions of $2018.

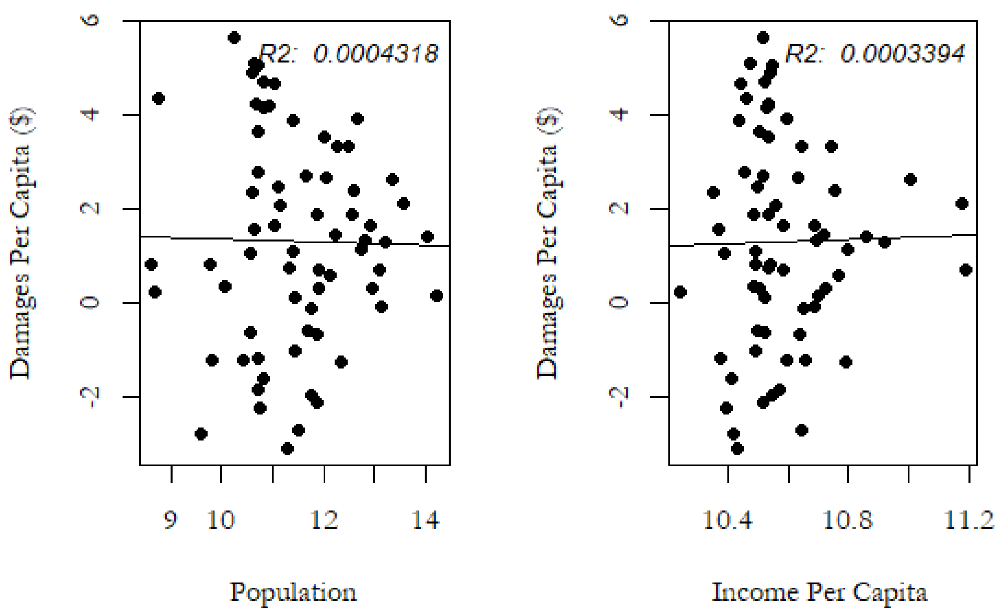

Figure 13: Per Capita Flood Damage vs. Population and Income Per Capita, 1996-2018

Notes: This figure shows the natural log of average yearly per capita property damages from flooding from 1996-2018 for each county in Pennsylvania vs. the natural log of population (left figure) and vs. the natural log of per capital income (right figure). All damage values are in millions of $2018.

Table 7: Per Capita Annual Flood Damage, 1996-2018

County	Metro	Per Capita
Wyoming	Scranton--Wilkes-Barre	$284.69
Susquehanna		$162.38
Jefferson		$160.58
Clarion		$134.82
Wayne		$111.71
Bradford	Sayre	$107.86
Sullivan		$77.29
Warren	Warren	$68.34
Venango	Oil City	$65.75
Pike		$64.37
Luzerne	Scranton--Wilkes-Barre	$50.95
Crawford	Meadville	$47.78
Mckean	Bradford	$38.93
Monroe	East Stroudsburg	$34.80
Lackawanna	Scranton--Wilkes-Barre	$27.80
Dauphin	Harrisburg-Carlisle	$27.69
Union	Lewisburg	$15.93
Lycoming	Williamsport	$15.16
Beaver	Pittsburgh	$14.51
Bucks	Philadelphia	$13.91

Notes: This table lists the top 20 counties in terms of yearly per capita property damages from flooding over the period 1996-2018. All property damages are listed in $2018.

While the previous results, for total losses, are instructive, it is also valuable, from a welfare and policy perspective, to examine losses on a per capita basis – having large total losses is certainly a cause for concern but it is an even bigger concern when those losses are spread over fewer people as this implies that each person is shouldering a larger share of the economic burden.[7] In Figures 12 and 13 and Table 7, we repeat the same analysis as before but this time we use per capita property losses in place of total losses. We generate the per capita values by taking total property damages and dividing by the mid-point of the population distribution for each county during our study period. We then further divide this value by 23 to get an average annual estimate. As before, the values in Figures 12 and 13 are in logged form, and Table 7 presents the unlogged, yearly values for the top 20 counties. Once again, these results show a

[7] We also conducted a third analysis (not shown) looking at yearly losses per capital as a share of real household income in each county. The results were qualitatively similar to the per capita results with more rural and poor counties bearing more of the economic load.

great deal of heterogeneity with higher losses in the Northeast and in the Susquehanna watershed. However, what stands out with these new results, as compared to those for total losses, is how much more concentrated the higher values are in rural counties. Looking at Table 7, we see that many of the counties in the top 20 are either outside of metro regions or are considered rural-fringe counties within their metro. The metro definition used in Tables 6 and 7 is from the U.S. Census Bureau. Using the definition of rural from the Center for Rural Pennsylvania (CRP, 2019), we find that for total losses only 9 of the 20 counties are considered rural, but for losses per capital that number rises to 16 out of 20. In addition, we do not see any real relationship between population or income per capita and losses per capita in Figure 14. To provide some context for these results, for Wyoming County the value of $284, which is the average yearly burden from flooding for each person in the county over the past 23 years, represents 0.94% of real income per capita.

5. Increased Flood Risk and Infrastructure Exposure in Pennsylvania

Flooding has been identified as one of the major sources of climate-related vulnerability, and historically has been the source of the majority of weather-related damages in Pennsylvania. In this section, we use data from multiple sources to summarize the exposure of different infrastructure systems in Pennsylvania to flooding, and in Section 6 we discuss drivers of future flood risk in Pennsylvania.

5.1 Current Infrastructure Exposure to Flood Risk

We began by examining the historical likelihood of waterways in Pennsylvania exceeding flood stage. To perform this analysis, we obtained streamflow and gauge height data for a number of different locations in Pennsylvania watersheds from the U.S. Geological Survey. We also focused our analysis on areas in Pennsylvania where flooding has caused substantial damage historically – Allegheny, Dauphin, Luzerne and Wyoming counties. We chose these four counties to capture both urban and rural areas of Pennsylvania, as well as specific areas of Pennsylvania (Luzerne and Wyoming counties) where flood damage per capita appears to be particularly high. The streamflow data that we use for this analysis is described in Table 8, and the representative stations that we use are shown in Figure 14. We use representative stations for this analysis; we found a high degree of correlation among stations along individual waterways. One advantage of using streamflow data over gauge height data is that there is a much longer history in the streamflow data (several decades of streamflow data for many locations, as opposed to around one decade of gauge height data). While the gauge height is the more precise measure of whether a waterway is above flood stage, we found a very strong correlation between gauge height and streamflow.

Table 8: Representative USGS Streamflow Data for Four Pennsylvania Counties

County	Station ID	Site Location	Starting Date	Ending Date	Streamflow Type	Flooding Threshold (cubic ft/second)
Wyoming	01533400	Susquehanna River at Meshoppen	10/1/76	6/1/19	Daily mean discharge (cubic ft/second)	120,000
Luzerne	01536500	Susquehanna River at Wilkes-Barre	1/1/70	6/1/19		110,000
Dauphin	01570500	Susquehanna River at Harrisburg	1/1/70	6/1/19		320,000
Allegheny	03086000	Ohio River at Sewickley	1/1/70	6/1/19		230,000

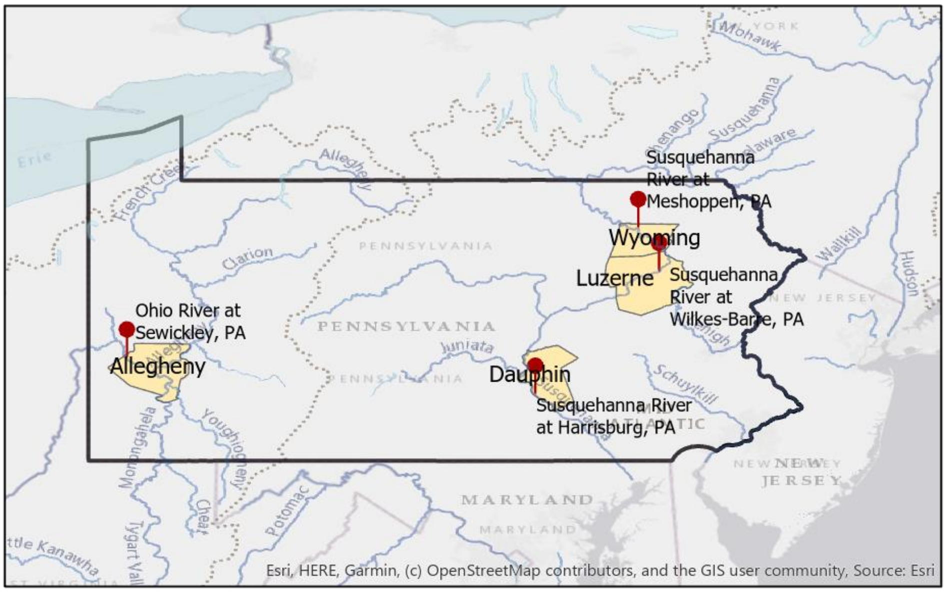

Figure 14: Locations of Representative Streamflow Stations for Four Pennsylvania Counties

Figure 15 shows the distribution of daily streamflows since 1970 in the four counties that we studied, along with an indication of conditions under which flood stage was likely reached or surpassed, based on the historical relationship between streamflow and gauge height. Figure 16 shows the change in extreme streamflow observations in the four counties that we studied. The figures show that the extreme observations in the streamflow distribution are quite large as compared to historically normal streamflows, with the most extreme observations being roughly twice as large as historical averages. The figures also show that flood events in these four counties have happened on far less than 0.5% of days during the 49-year period over which we have streamflow data. The magnitude of these extreme events also does not appear to have changed substantially in the past five decades or so.

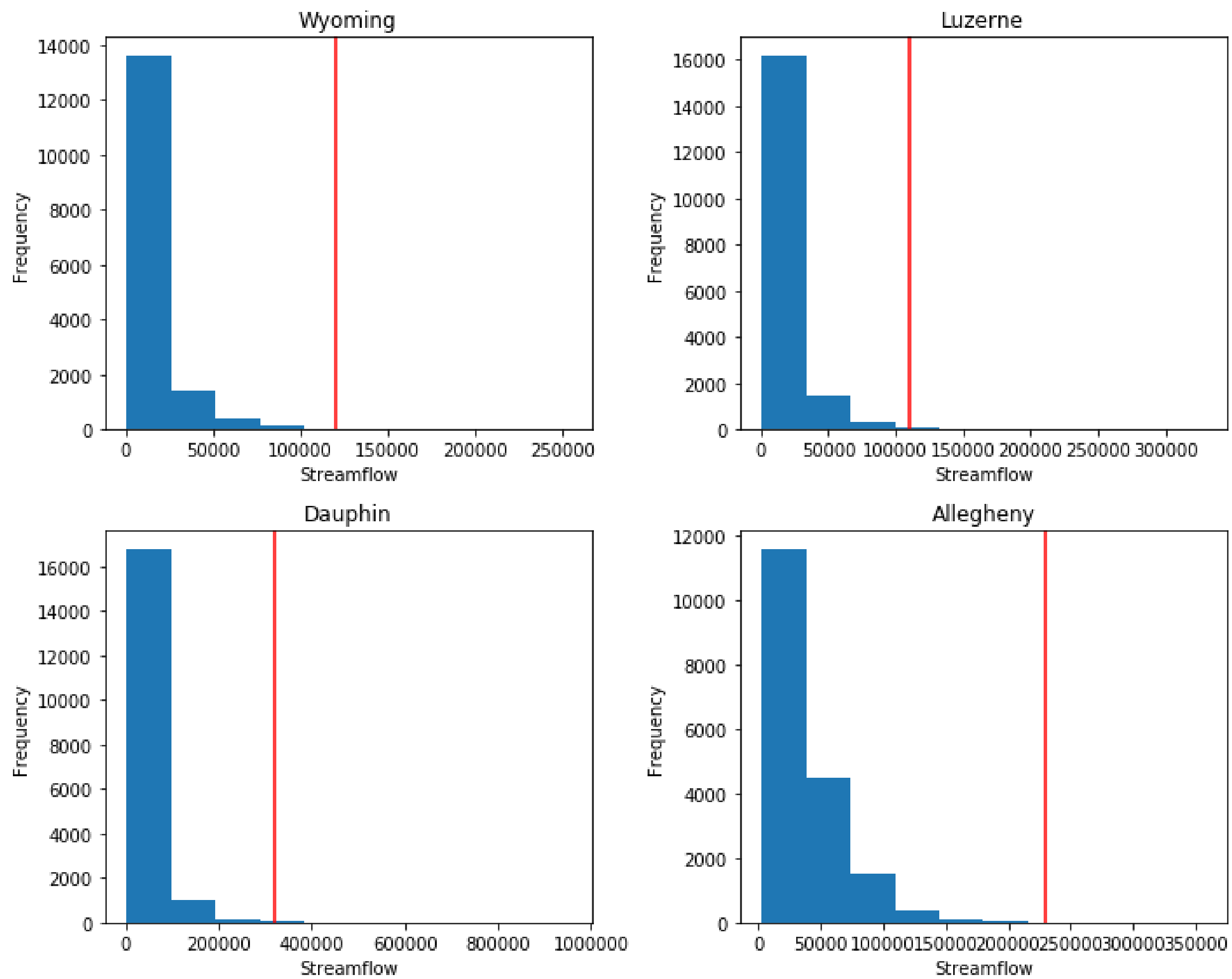

Figure 15: Histogram of daily streamflows (cu. ft/s) in four Pennsylvania counties, 1970-2019 (May). The red lines show the streamflow levels that are statistically associated with the river systems operating above flood stage, based on gauge height data.

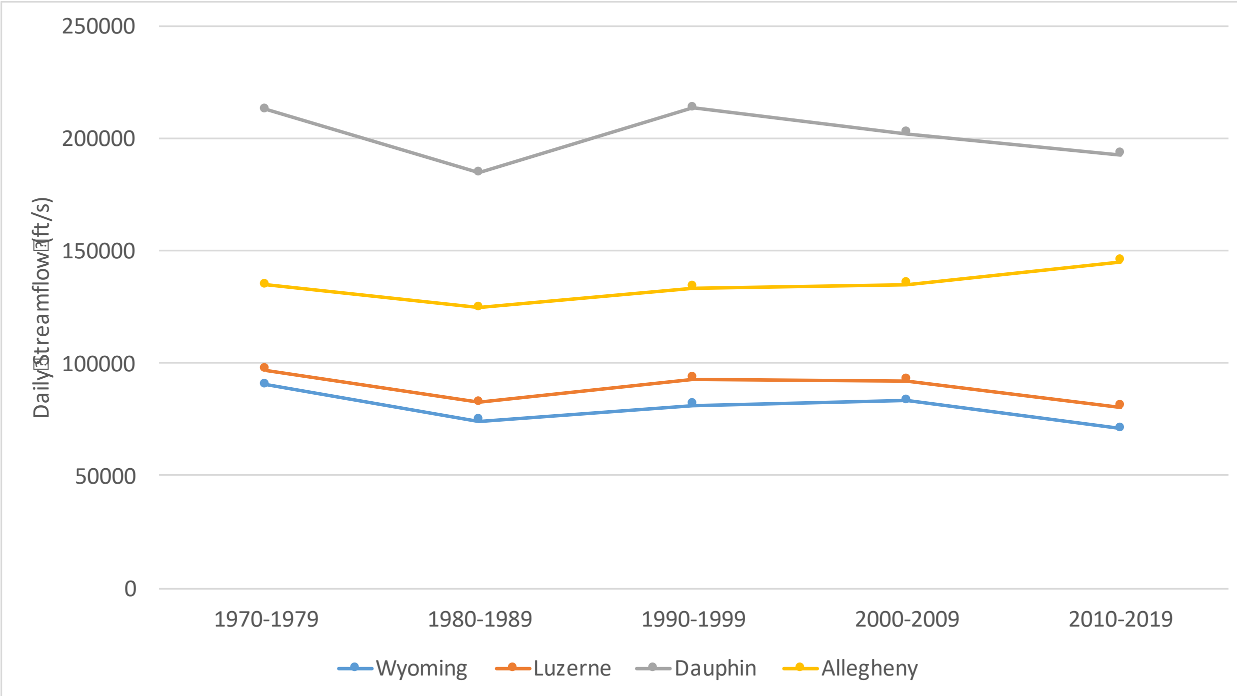

Figure 16: Change in the highest streamflow levels by decade in four Pennsylvania counties. The figure plots the streamflow levels in each county that were observed 1% of the time or fewer in each county.

While the levels of extreme streamflow events have not changed substantially in the past five decades, the frequency with which these high streamflow levels are attained has changed. Figure 17 shows the number of days in each decade that streamflows were in the highest 5% of all recorded daily streamflows in that county. There has been some volatility over time in when these extreme streamflows have been recorded, but more extreme streamflow observations have been recorded in Wyoming county during the previous two decades.

The conclusion from Figures 14 to 16, particularly in light of analysis of flood damage in Section 4, is that there is no evidence from several decades of streamflow data that changes in climate over several decades have made flood situations are becoming more common among the major waterways in Pennsylvania. There is short term variation as weather patterns change year to year. The damages from flooding, however, have risen along with population and income. Heavier precipitation episodes, as discussed in Shortle et al. (2015) would suggest a higher potential for flooding episodes. These flooding episodes may be more localized or concentrated among smaller waterways that have not been monitored over as long a period as major waterways.

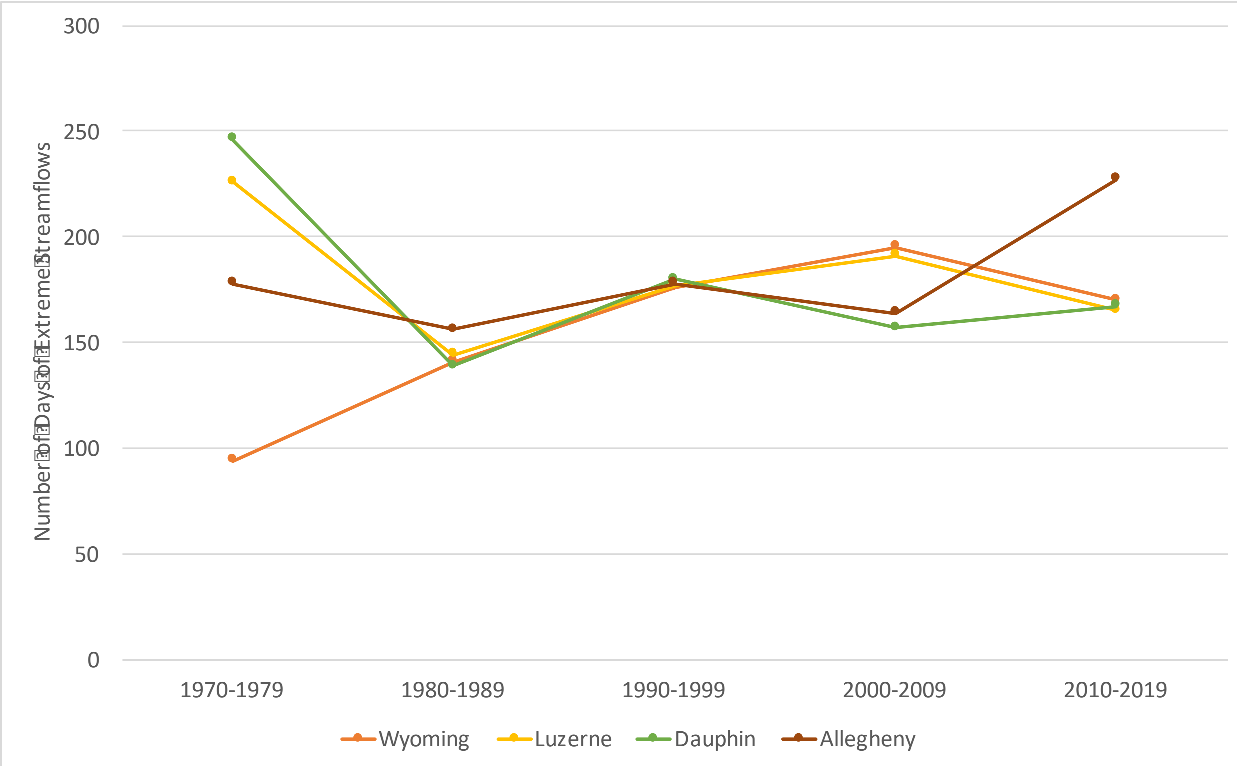

Figure 17: Frequency of daily streamflows exceeding the 5% largest streamflow observation between 1970 and 2019 (May) in four Pennsylvania counties.

Using data from the U.S. Energy Information Administration Energy Mapping System as well as FEMA-identified flood zones, we are able to identify some elements of Pennsylvania infrastructure that appear to be at particular risk of flooding. These identified infrastructure elements are those that were found to be located inside a designated flood zone based on an overlay of geolocated infrastructure with the locations of the flood zones. We show this for power plants, petroleum and natural gas infrastructure, and rail in Figures 18 to 20. Each of the figures shows the location of infrastructure inside and outside of flood zone areas, as well as an overlay of the relevant river basin.

Figure 18 in particular shows that there is a wide distribution of power plant infrastructure located within flood zones in Pennsylvania. While there are dozens of such plants, most of them are very small in capacity (less than 15% of this capacity is in plants that are 100 MW or greater). The sum total of the power generation capacity located in flood zones in Pennsylvania is 5,400 MW, which is greater than 10% of all of the generation capacity located in Pennsylvania and around 3% of capacity in the regional PJM power grid.

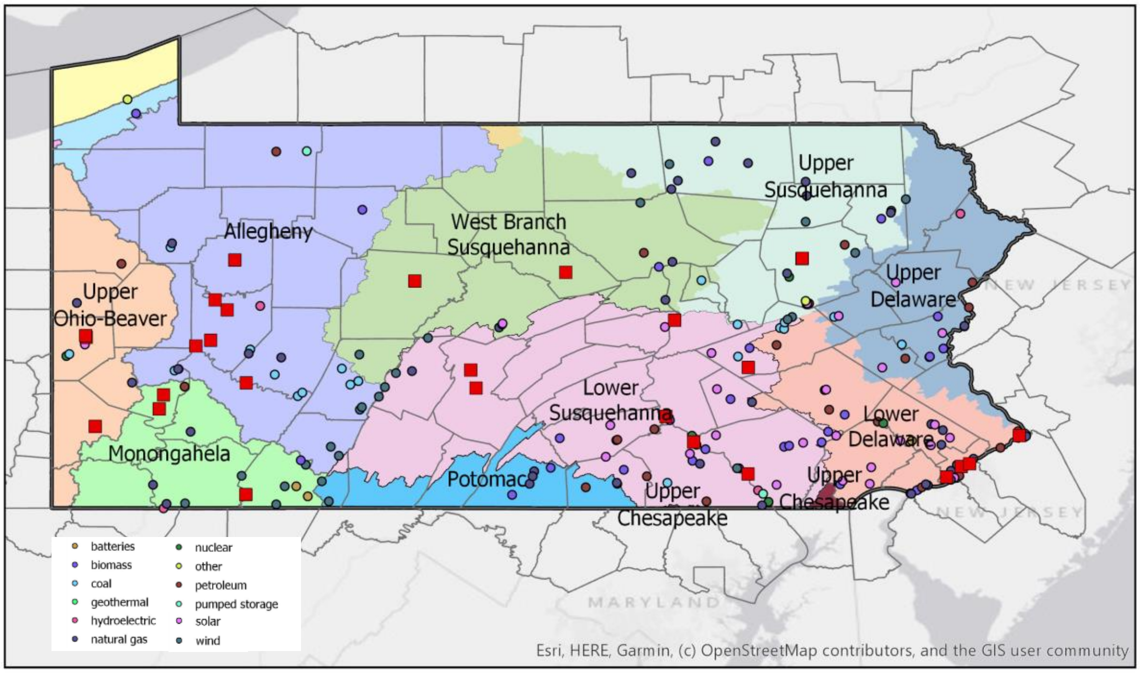

Figure 18: Power plants in Pennsylvania. Plants located in identified flood zones are marked with red squares.

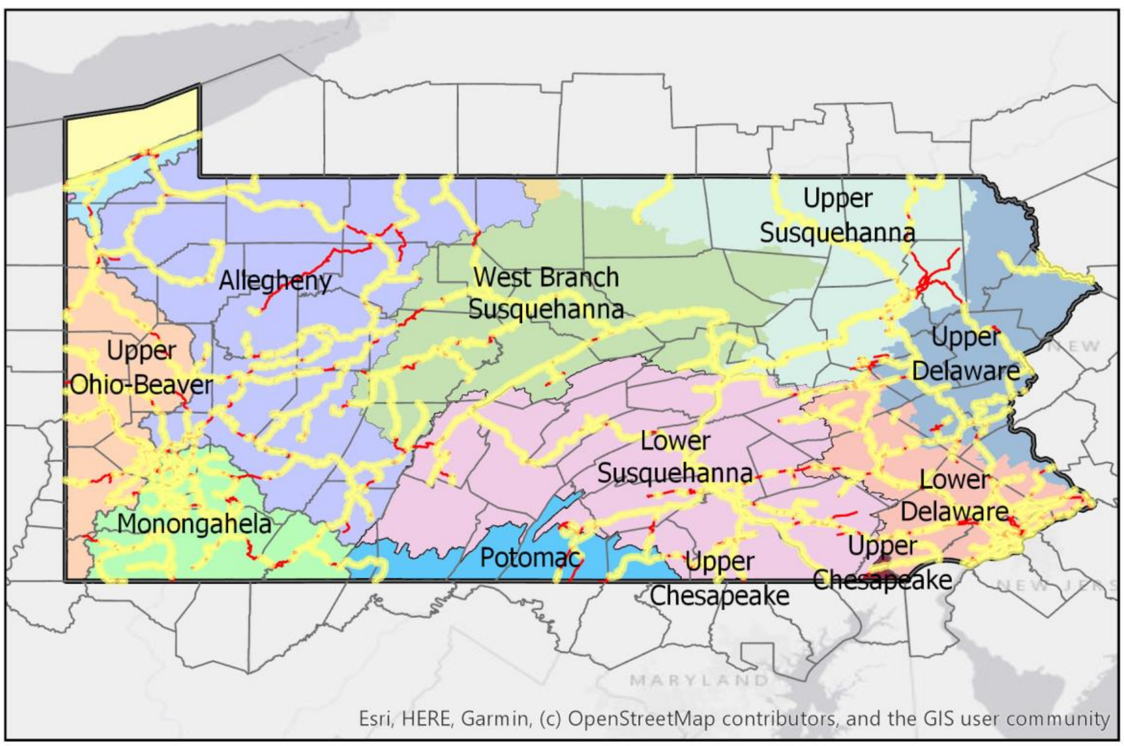

Figure 19: Rail Infrastructure in Pennsylvania. The yellow areas correspond to rail segments that lie wholly or partially in flood zone locations. The red areas correspond to rail segments that lie wholly outside of flood zones.

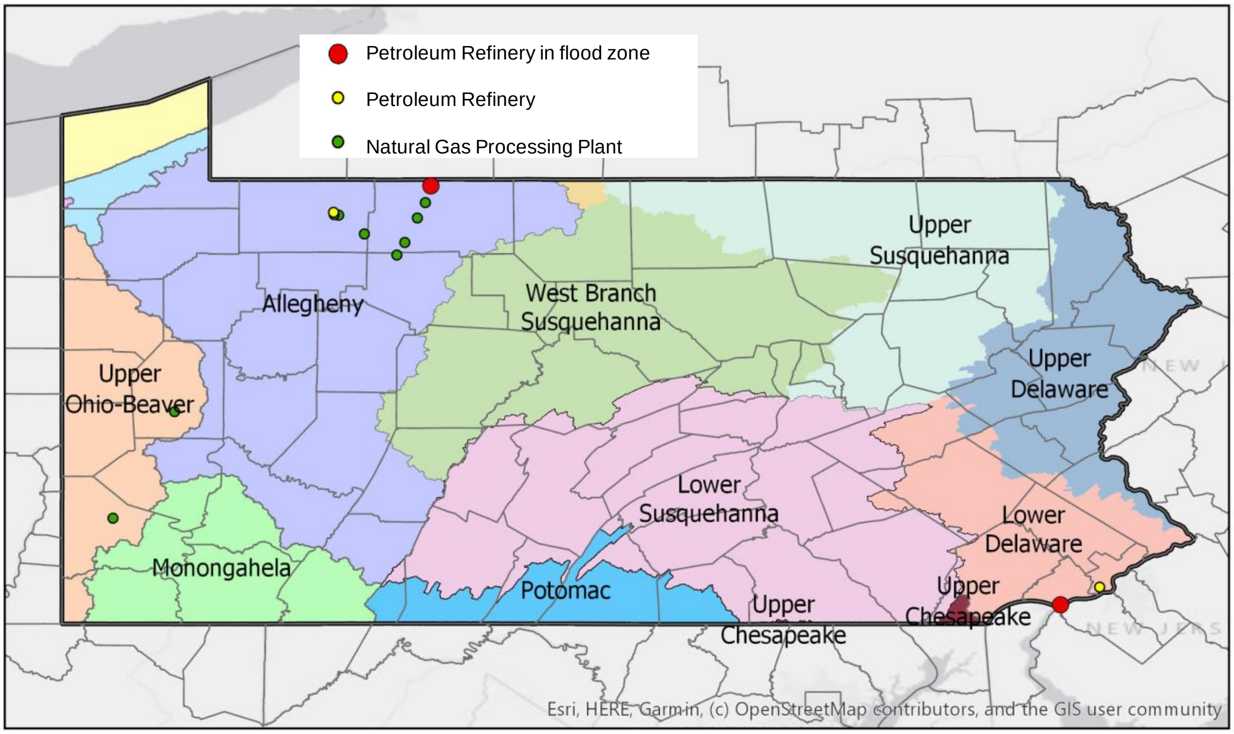

Figure 20: Petroleum refineries and natural gas processing plants. The larger red dots indicate refineries that are currently located in flood zones. No natural gas processing plant in Pennsylvania was identified as currently operating in a flood zone.

Because of its hilly and steep topography, heavy precipitation events can also lead to an increased risk of landslides in Pennsylvania. Landslide risk maps place Southwestern Pennsylvania (all or portions of Allegheny, Fayette, Greene and Washington counties) at particular risk from landslides, since the frequency and severity of landslides in this region are both high relative to other areas of the state. Landslides can have direct impacts on transportation infrastructure in particular since many roadways and railways have been built to follow the contours carved out by rivers. Landslides can also have unexpected and indirect effects on subterranean infrastructure (including natural gas pipelines and buried conduit for electric distribution or communications networks) triggered by low-grade seismic activity that can be associated with large landslides.[8]

Figures 21 to 23 show the location of electrical, railway and natural gas infrastructure in landslide hazard zones in Pennsylvania.

[8] Such events appear to be highly uncommon, though at least one natural gas pipeline interruption in West Virginia has been attributed to landslides. See https://www.eenews.net/stories/1060472727.

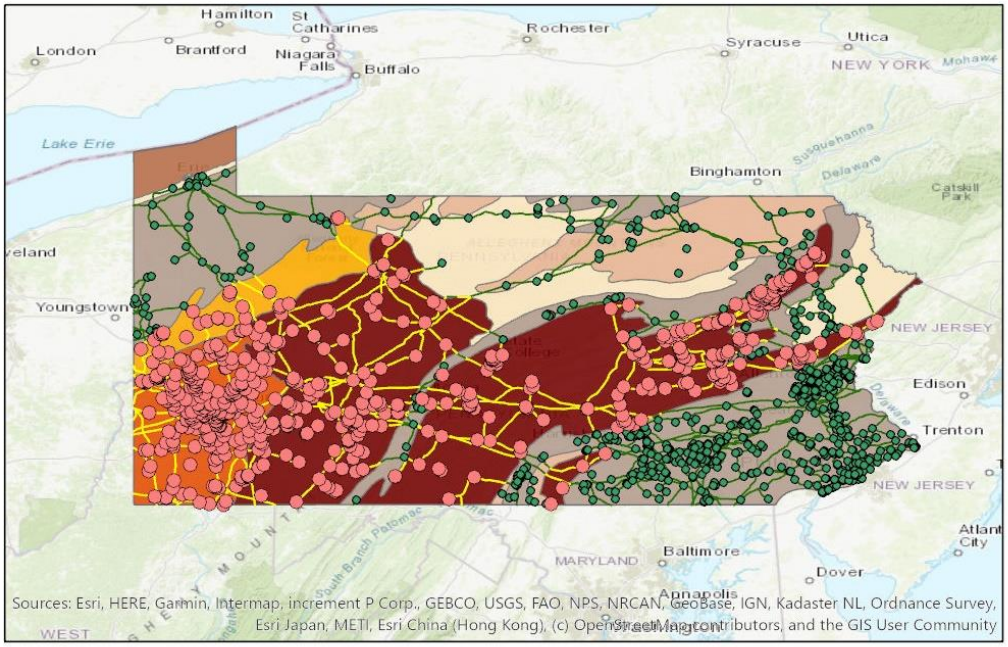

Figure 21: Electric power substations in identified landslide hazard areas (red dots) and electric transmission lines whose support towers are in identified landslide hazard areas (yellow lines). Green dots and green lines indicates substations and transmission lines that lie outside of identified landslide hazard areas.

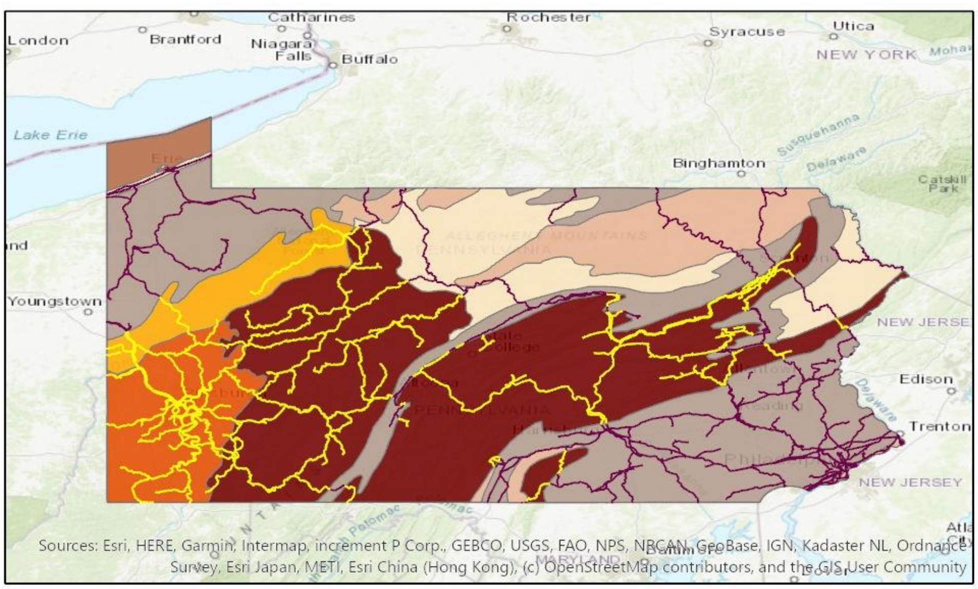

Figure 22: Railroads in identified landslide hazard areas (yellow lines). Purple lines indicate railroads that lie outside of identified landslide hazard areas.

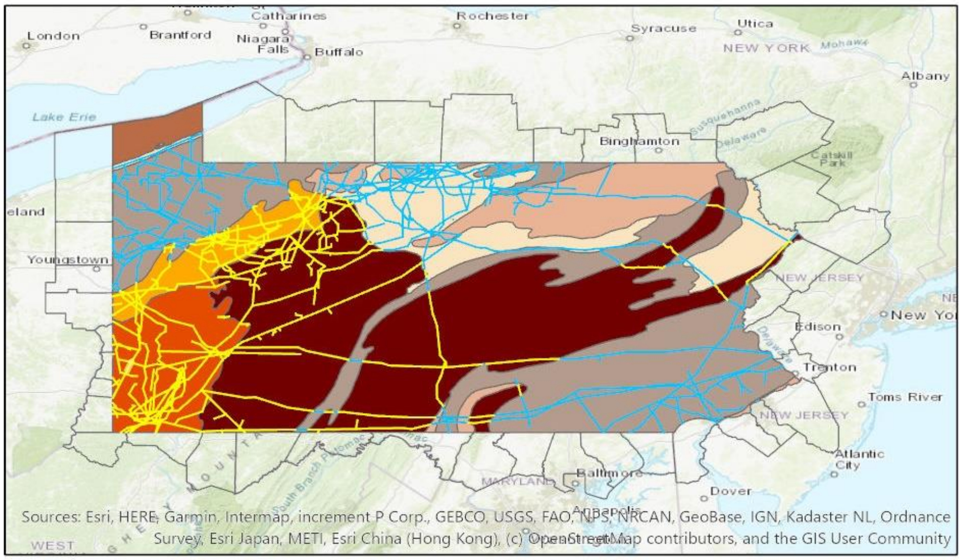

Figure 23: Natural gas pipelines in identified landslide hazard areas (yellow lines). Blue lines indicate natural gas pipelines that lie outside of identified landslide hazard areas.

Table 9 summarizes the relative amount of different energy and transportation infrastructures that lie within identified flood zones or landslide hazard zones. Not all information is available for all infrastructure systems, and geolocation of some types of local infrastructure (such as water treatment plants and low voltage electric distribution substations) is not readily available in the public domain.

Table 9: Exposure to Flood and Landslide Hazard Zones for Selected Energy and Transportation Infrastructure

	Proportion in Flood Zone	Proportion in Landslide Hazard Zone
Electric Power Plants (% of capacity)	3.40%	N/A
Electric Transmission (% of line-miles)	5.29%	49.25%
Electric Substations	6.16%	41.16%
Natural Gas Pipelines (% of pipe-miles)	5.00%	49.64%
Natural Gas Compressor Stations	5.79%	N/A
Natural Gas Processing Plants	0.00%	N/A
Petroleum Refineries	50.00%	N/A
Petroleum Product Pipelines (% of pipe-miles)	7.65%	N/A
Railroads (% of rail-miles)	36.47%	55.29%

6. Conclusions and Information Needs

This report has reviewed the potential ways in which extreme weather may impact the ability of infrastructure in Pennsylvania to deliver needed services. We have synthesized the conclusions of a number of large-scale studies of climate change and infrastructure, with as much specific application to Pennsylvania as possible. We have also examined historical data on damages from flooding, which multiple studies have identified as a dominant risk factor facing infrastructure in Pennsylvania and the U.S. northeast in a changing climate. Our analysis of flood damages suggests that over the state as a whole, flood-related impacts over the past decades have changed along with population and income. The likelihood of flooding events does not appear to have changed substantially in the past several decades, but the projected changing nature of rainfall patterns in Pennsylvania suggests that these events are likely to increase in frequency (if not severity) in the coming decades as the climate changes. Information on the drivers of this change is limited and more research is needed, but the available evidence to date suggests that increased flood risk is likely to be driven by Atlantic hurricane activity.

While it is difficult to develop very specific risk projections because of a limited amount of data specific to Pennsylvania, based on the available evidence, we conclude that in the near term flooding, drought and extreme heat are likely to be the most substantial stressors for Pennsylvania infrastructure. Whether drought continues to be a substantial stressor in the long term depends on the pace of technological change in the regional power grid. Experience with recent severe storms and flooding events demonstrates how local electricity infrastructure may be more susceptible to climate-induced vulnerabilities than the regional bulk power grid. While Pennsylvania is largely not a coastal state, its dependence on fuel and other commodity transportation infrastructure from coastal states leaves it economically vulnerable to transportation disruptions. Pennsylvania also has important fuel supply infrastructure, transportation infrastructure and a major population center in Southeastern Pennsylvania, which has been identified as an area vulnerable to both sea level rise and coastal storm surge.

Developing more detailed infrastructure risk assessments for Pennsylvania depends in part on the availability of better models of future extreme weather events and flood patterns, which is a difficult task requiring more fundamental research. More research and additional data is also needed to support decision-making at relevant scales that is able to incorporate potential vulnerability implications for long-lived infrastructure investments. While a few examples of this kind of anticipatory no-regrets decision-making have been identified in ways that reduce stress on local stormwater systems and increase the resilience of commercial-scale distributed energy systems, this kind of planning is by and large not performed for large-scale infrastructures such as pipelines, power grids and rail.

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Chapter 4 Review of Past and Potential Future Precipitation Changes in Pennsylvania

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1. Motivation

Pennsylvania has frequently experienced severe floods (Ahmadalipour and Moradkhani, 2019; Quinn et al., 2019). For the period of 1959 to 2005, Pennsylvania ranked 2nd, 10th, and 14th in the U.S. in the frequency of flash flood-related fatalities, injuries, and casualties, respectively (Ashley and Ashley, 2008). Within the same period, two of the ten deadliest events in the U.S. (excluding hurricane Katrina) have happened in Pennsylvania, resulting in over 50 fatalities (Ashley and Ashley, 2008). One was a flash flood in 1977 and the other was a flood caused by Tropical Storm Agnes in 1972. Between 1975 and 2019, the Federal Emergency Management Administration (FEMA) paid $953 million to National Flood Insurance Program (NFIP) policyholders in Pennsylvania for property damages (FEMA, 2019).

Deadly floods with the highest impact on humans have resulted from extreme precipitation (Ashley and Ashley, 2008; Doocy et al., 2013; Špitalar et al., 2014). Extreme precipitation is quantified in a number of ways, including the number of days with daily precipitation above the 95th or 99th percentile of precipitation records, the total precipitation amounts on such days, or the total precipitation on the wettest five-day periods (Agel et al., 2015; Diffenbaugh et al., 2017; Ning et al., 2015; Winter et al., 2019; Zarekarizi et al., 2017). Extreme precipitation events are increasing in many regions around the world (Berghuijs et al., 2017; Easterling et al., 2007; Hayhoe et al., 2018) including Pennsylvania (Hayhoe et al., 2007; Peterson et al., 2013; Shortle et al., 2015). This highlights the importance of understanding extreme precipitation mechanisms that generate floods. An improved understanding of extreme precipitation processes also helps enhance infrastructure design and urban planning (Maimone et al., 2019), which rely heavily on precipitation simulations at a high spatiotemporal resolution.

This chapter reviews information about precipitation extremes in Pennsylvania. We summarize past studies with a focus on changes in average and extreme precipitation. We start by reviewing observed and projected changes in precipitation. We then proceed with a review of recent research on local-level decisions that depend on precipitation simulations. After discussing the role of uncertain factors in such decisions, we conclude with a list of open research questions.

2. Overview of flooding and extreme precipitation in Pennsylvania

The primary sources of water in flood events include rainfall, as well as river-, ocean- and ground-water. Ground-water flooding is caused by factors such as storm sewer backup, pipe break, or high ground-water levels which may, for example, manifest itself through water infiltration into basements or spring overflow (Macdonald et al., 2012). Coastal flooding happens when normally dry land areas along a coastline are flooded by ocean water brought by storm surges (Brown et al., 2019). Pluvial flooding can result from rain-on-snow events or from direct rainfall on the snow-free land. The latter could be in the form of soil moisture saturation or exceeding infiltration capacity that is common in impervious urban areas (Buchanan et al., 2018). Riverine flooding can result from snowmelt, dam failure, deliberate release from dams, levee failure, ice damming and the break-up of ice jams, or high flows due to upstream rainfall. The dominant mechanisms of river flooding in Pennsylvania are snowmelt and upstream precipitation (Berghuijs et al., 2016).

Most floods in Pennsylvania are attributed to extreme precipitation (Berghuijs et al., 2016). Extreme precipitation events in the Northeast U.S. show a strong seasonality. The largest fraction (46%) of such extremes happen in summer. 44%, 7%, and 3% of extreme precipitation events happen in fall, spring, and winter, respectively (Kunkel et al., 2012). These floods could be in the form of either extreme rainfall on normally-dry land areas, rain on snow, or overflow from streams (i.e. riverine flooding). In this chapter, we focus on floods from extreme precipitation.

Studies on the relationship between extreme floods and synoptic-scale weather patterns show that three main causes of annual extreme precipitation in the Northeast U.S. are fronts, tropical cyclones (TCs), and extratropical cyclones (Kunkel et al., 2012). Frontal systems form when warm and cold air masses meet. TCs are non-frontal cyclones with warm cores. The energy source of a TC is latent heat from the condensation of evaporated ocean water (National Hurricane Center, 2019). Extratropical cyclones have cold air at their core and move poleward; their energy source is from the interaction of cold and warm air masses (baroclinic processes) (National Hurricane Center, 2019). Extratropical cyclones include events such as winter west coast storms and nor'easters.

The most extreme floods throughout the eastern U.S. are often driven by precipitation extremes resulting from TCs (Dhakal, 2019; Kunkel et al., 2010; Schelf et al., 2019; Smith et al., 2010). Historically, these have caused 36%, 35%, and 44% of annual, summer, and fall extreme precipitation events (Kunkel et al., 2012). Even though very rare extreme events are associated with TCs, only around 5-15% of annual flood peaks at U.S. Geological Survey (USGS) streamflow gages in Pennsylvania are caused by TCs (Smith et al., 2010). This is because most riverine flood peaks occur in winter and spring with a combination of rain-on-snow, snowmelt, and storms (Smith et al., 2010). Additionally, TCs often take place in fall and autumn storms are less capable of producing flood peaks mainly due to low antecedent soil moisture (Smith et al., 2010).

Extratropical cyclones are characterized by extreme precipitation events in the vicinity of a low-pressure system center (Kunkel et al. 2012). Extratropical storms cause only 16% of extreme precipitation events (Kunkel et al., 2012). Extratropical-related extreme events are mainly apparent in the fall. They cause about 14%, 12%, 41%, and 47% of fall, summer, spring, and winter extremes, respectively (Kunkel et al., 2012). Even though extratropical storms are not very common in spring and winter (only 3% and 7% of extreme precipitation events happen in winter and spring), most of the riverine flood peaks are associated with extratropical storms (Kunkel et al., 2012; Smith et al., 2010). Around 40% of streamflow flood peaks are caused by winter-spring extratropical systems. This could be due to the additional impacts of rain over snow and snowmelt (Smith et al., 2010). While fall and summer extratropical-related extremes are more common, they are less capable of generating streamflow peaks because of low antecedent soil moisture (Kunkel et al., 2012; Smith et al., 2010).

Fronts are characterized by sharp temperature gradients and wind shifts (Kunkel et al., 2012). Fronts frequently cause precipitation extremes in the Northeast U.S. 47% of annual extreme precipitation events are caused by fronts while TCs and extratropical cyclones cause only 36% and 16% of those events (Kunkel et al., 2012). Front-related extremes are evenly distributed throughout the year. 42%, 49%, 59%, and 53% of extreme events in fall, summer, spring, and winter respectively are caused by fronts (Kunkel et al., 2012).

3. Historical trends in precipitation and flooding in Pennsylvania

Average precipitation has increased overall in the U.S. and in the Northeast U.S. (Fernandez and Zegre, 2019; Goodwell and Kumar, 2019; Hayhoe et al., 2018; Kang and Sridhar, 2018). Total precipitation over the coterminous U.S. increased at a rate of 4.5 mm/decade between 1901 and 2006 (Easterling et al., 2007). In the Northeast U.S., observations show a precipitation increase of 9.5 (±2) mm/decade (Keim et al., 2005; Hayhoe et al., 2007). In this region, winter precipitation observations between 1950 and 1999 show a decreasing trend of 0.5 (±1) mm/decade, summer precipitation shows an increasing trend of 1.2 (±0.5) mm/decade, and spring/fall precipitation records indicate an increasing trend of 2.4 (±0.3) (Hayhoe et al., 2007). Over the past century, average annual precipitation in Pennsylvania has increased by 10% and in some parts, such as the southeast of the commonwealth, there is a general wetting trend (less frequent droughts and more frequent very wet conditions) (Kang and Sridhar, 2018; Shortle et al., 2015).

Studying extreme precipitation is important as it drives risks for human lives and properties through disastrous floods and snowstorms (Changnon et al., 2006; Hayhoe et al., 2018; O'Gorman, 2014). Intensification of the global hydrologic cycle due to anthropogenic climate change is expected to increase extreme precipitation (Hayhoe et al., 2007; 2018; Huntington et al., 2006). Changes in mean precipitation are not linearly correlated with changes in extreme precipitation (Wehner, 2004). Hence, extremes need to be explored somewhat separately from mean precipitation.

Overall, frequency and magnitude of extreme precipitation observations in the U.S. show an upward trend in the 20th century (Groisman et al. 2004; 2005; 2012; Hayhoe et al., 2018; Janssen et al., 2014; Kunkel et al. 2003, 2007). The rate of this increase is higher than the rate of increase in average precipitation (Kharin et al., 2007; 2013; Shortle et al., 2015). Observed precipitation extremes in the Northeast U.S. follow a similar upward trend (Goodwell and Kumar, 2019; Griffiths and Bradley, 2007; Hayhoe et al., 2007; Janssen et al., 2014; Kunkel et al., 2013; Ning et al., 2015) especially in summer (Frei et al., 2015; Hoerling et al., 2016). The upward trend in extreme precipitation in the Northeast U.S. is greater than that of any other region in the U.S. (Hayhoe et al., 2018; Horton et al., 2014; Janssen et al. 2014).

In the Northeast U.S., observed increases in heavy precipitation are reported to be 55% between 1958-2018 (Hayhoe et al., 2018). Another study reports that heavy precipitation has increased by more than 70% between 1958-2010 (Horton et al., 2014). Additionally, more heavy rain events are occurring during the summer (Hoerling et al., 2016).

Additional studies have analyzed trends of extreme precipitation events caused by particular synoptic-scale weather patterns. For example, Knight and Davis (2009) and Kunkel et al. (2010) find an upward trend in TC-related extreme events. This trend becomes statistically significant to the east of the Appalachians (Kunkel et al., 2010). Extremes caused by frontal and extratropical cyclones in the Northeast U.S. also show a statistically significant upward trend (Kunkel et al. 2012).

4. Future projections of precipitation and flooding in Pennsylvania

Modeling precipitation changes is typically more difficult than other atmospheric variables (e.g. temperature) (e.g., Hayhoe et al., 2007; Ross et al., 2013; Winter et al., 2019). This section focuses on projected trends in precipitation in the Northeast U.S. including Pennsylvania. General Circulation Models are commonly used for projecting precipitation. Due to their coarse resolution, dynamical downscaling, empirical-statistical downscaling, or other methods are often used to estimate precipitation projections at higher resolutions (Knutson et al., 2015; Ning et al., 2015). Average and heavy precipitation projections show an increase by the late 21st century (Hayhoe et al., 2018; Martel et al., 2019). These projections provide some information, but they are still subject to uncertainties. It is important to take these uncertainties into consideration. These uncertainties result from many sources such as structural uncertainty and the uncertainty in human activity. This kind of uncertainty is often referred to as “deep uncertainty” (Lempert, 2002). Representing these deep uncertainties can be important in decision-making.

General Circulation Models (GCMs) are widely-used tools for generating projections of future climate. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR4) (IPCC, 2007) relies on climate model results from the Coupled Model Intercomparison Project Phase 3 (CMIP3). For the Fifth Assessment Report (AR5), more complex models from the fifth version of the CMIP (CMIP5) were used (Knutti and Sedláček, 2013). GCMs are typically run at rather coarse spatial resolutions which may result in poor skill at local scales. Dynamical (Knutson et al., 2015) and empirical (Emanuel, 2013; Ning et al., 2015) downscaling methods are used to enhance GCMs resolutions.

Dynamical downscaling methods nest a Regional Climate Model (RCM) within a GCM (Lee et al., 2018; Wood et al., 2004). In parallel to CMIP, the Coordinated Regional Downscaling Experiment (CORDEX) provides regional-scale climate simulations using RCMs for 14 domains around the world, including North America (Lee et al., 2018). Other sources of dynamically downscaled simulations are the North American Regional Climate Change Assessment Program (NARCCAP) and USGS RCM simulations (Hostetler et al., 2011). While dynamical downscaling methods are advantageous because they are physically-based, one drawback is that they are computationally expensive (Tryhorn and DeGaetano, 2011).

Empirical downscaling approaches use statistical methods to establish a relationship that matches a GCM's coarse simulations to local-level observations (Najafi et al., 2011). A common method of empirical downscaling is bias correction (Wood et al., 2004). While empirical downscaling methods are less computationally demanding, their weakness is that the established relationship is assumed not to change in time (Tryhorn and DeGaetano, 2011).

For some applications, precipitation projections with very high spatiotemporal resolution are needed and even RCMs do not provide the necessary resolution. Stormwater management and urban infrastructure design are two examples where RCMs underestimate precipitation at sub-daily scale (Mishra et al., 2012). Hence, there are several alternative approaches to produce high-resolution precipitation projections that do better on the sub-daily time scale. For example, Thorndahl et al. (2017) use statistical models to project precipitation. They generate historical and future simulations of precipitation by resampling from historical observations so that the statistical properties are replicated. Similarly, the Philadelphia Water Department (PWD) uses the differences between observations and historical simulations from climate models and calculates factors that are applied to generate high-resolution hourly precipitation projections (Maimone et al, 2019).

Global evaluations of the CMIP3 and CMIP5 ensembles do not show a considerable difference between the two sets of experiments (Knutti and Sedláček, 2013). A weakness of both ensembles is that they tend to underestimate historical trends in extreme precipitation (Janssen et al., 2014; Min et al., 2011). Evaluations of CMIP3 and CMIP5 precipitation simulations in Pennsylvania indicate a wet bias in both experiments (e.g., Ross et al., 2013; Shortle et al., 2009; 2015). The performance of empirically- and dynamically downscaled simulations have also been assessed for Pennsylvania. NARCCAP RCMs show a wet bias across the state (Ross et al., 2013). These biases are, perhaps, expected as these RCMs use information from CMIP3. Dynamically downscaled precipitation simulations from USGS RCMs are close to observations (Shortle et al., 2015). Empirically downscaled CMIP5 models in Pennsylvania are shown to perform better than dynamically downscaled models (Shortle et al., 2015).

CMIP5 models used in the previous Pennsylvania Climate Impact Assessment (PCIA) project a continuation of the upward trend in average precipitation (Shortle et al., 2015). The rate of change varies in space and time. Almost all atmosphere-ocean general circulation models (AOGCMs) (Hayhoe et al., 2007) show wetter winters. Changes in winter and spring precipitation are projected to be larger than changes in summer and fall precipitation where no change or decrease is projected (Hayhoe et al., 2007). The average precipitation in Pennsylvania is projected to increase by 15-20%, 10-15%, 0-5%, and 0-5% in winter, spring, summer, and fall, respectively by the late 21st century and under high emissions scenario (Representative Concentration Pathway 8.5) (Hayhoe et al., 2018). Empirically downscaled CMIP5 models used in the last PCIA project higher precipitation changes in the far eastern part of Pennsylvania (Shortle et al., 2015).

Studies on projections of precipitation extremes have used a percentile-based definition of extremes (Zarekarizi et al., 2017), Extreme Value Theory (EVT) (Kao and Ganguly, 2011; Kharin et al., 2007), or the Clausius-Clapeyron (CC) relationship (Liu et al., 2009). Climate models project that extreme precipitation events will become more intense (Kharin et al., 2007; 2013) and frequent (Allan and Soden, 2008; Chou et al., 2007) as a result of anthropogenic warming. For the period 2080-2099, the frequency of historical 20- and 100-yr storms is projected to increase tenfold for half of the globe, including the Northeast U.S. and Pennsylvania (Martel et al., 2019). These increases in frequencies are notable for the Northeast U.S. especially for short-term (1-day) storms (Martel et al., 2019).

Precipitation projections are deeply uncertain (Hawkins and Sutton, 2011; Knutti and Sedláček, 2013). Key sources of uncertainty include model uncertainty, emission uncertainty, and natural variability.

Model structure uncertainty is related to the limited ability of climate models to represent precipitation mechanisms (Kao and Ganguly, 2011). Suppose, for example, two climate models are run with the same initial conditions and forcings. Their projections will still differ due to model structure uncertainty (Hawkins and Sutton, 2011). Our lack of understanding of coupled human and natural systems, relationships to greenhouse-gas emissions, and interactions between climate and the Earth systems (Bhatia and Ganguly, 2019) all contribute to model uncertainty. Emission uncertainty arises from a lack of knowledge about the future release of greenhouse gases; this, in turn, impacts uncertainty surrounding future radiative forcings[9] (Hawkin and Sutton, 2009; Ho et al., 2019). Intrinsic or natural variability in climate appears as fluctuations in precipitation, for example, and reduces predictability (Deser et al., 2012). Natural variability adds uncertainty to the analysis of trends in precipitation simulations because it is difficult to distinguish long-term trends from noise effects (Hayhoe et al., 2007). These fluctuations can mask the anthropogenic trends for decades (Hawkins and Sutton, 2009; 2011). Another factor that adds uncertainty to extreme precipitation trend analysis is the sparsity of observations and

[9] The changes in the earth's incoming and outgoing energy at the top of the atmosphere (IPCC, 2018)

the sensitivity of trend detection methods to the length of data (Hayhoe et al., 2007; Wehner, 2004).

A common approach to representing some of these uncertainties is to build an ensemble of different models with different choices (e.g., about parameter values, initial conditions, and forcings) and then assume that the spread of that ensemble represents the uncertainty in simulations. This kind of uncertainty quantification is limited, for example, by the ensemble size (Her et al., 2019; Kharin et al., 2007).

5. Local-level decisions and the role of precipitation projections

Decisions about adaptation to climate change can hinge on estimates of future precipitation extremes (Mishra et al., 2012). Failures of urban infrastructure are often driven by heavy precipitation (Wang et al., 2019). Municipalities, cities, and states are the main actors in such decisions. For example, many municipalities are considering sewer capacity upgrades because of flooding and health concerns (Mainmone et al., 2019). To do so, hydrologic and hydraulic modeling is required, which requires projected precipitation timeseries with high temporal (typically an hour or less) and spatial resolution (Mainmone et al., 2019). Other applications of high-resolution precipitation projections include designing new storm sewer networks as well as estimating changes in flood frequency, pollutant loads, expected loads to wastewater, and frequency of combined sewer systems overflow (Maimone et al., 2019).

There is a considerable gap between the resolution required for urban infrastructure management and climate model resolutions (Mainmone et al., 2019). Current GCMs outputs are not directly applicable in stormwater management applications (Zahmatkesh et al., 2015). This is mainly because of their low spatiotemporal resolution that smooths out extremes. Low spatial resolution diminishes the intensity of local storms. Low temporal resolution leads to the inaccurate simulation of flash floods, which are projected to be affected the most by climate change (Maimone et al., 2019). Additionally, many fine-scale processes are not mechanistically resolved in GCMs. Thus, GCMs outputs need to be downscaled (Cloke et al., 2013).

RCMs have a finer resolution than GCMs. However, their resolution is typically still too coarse for many stormwater management applications. Additionally, their representation of climate processes is similar to that of GCMs (Cloke et al., 2013), limitations of which were discussed above. Thus, statistical methods are developed to address this scaling issue (Maimone et al, 2019; Thorndahl et al., 2017; Wang et al., 2019). These approaches range from empirical downscaling (Fowler et al., 2007; Zahmatkesh et al., 2015) to bias correction (Cloke et al., 2013). Another approach is to multiply stationary-based Intensity-Duration-Frequency (IDF) curves by a constant change factor derived from the established relationship between a certain GCM's historical simulations and future projections (Maimone et al., 2019; Zahmatkesh et al., 2015).

Current flood hazard projections are deeply uncertain (Hawkins and Sutton, 2011; Ruckert et al., 2019). This does not imply, however, that decisions (for example about the design of infrastructure) cannot be improved by considering these deeply uncertain projections (Keller and Nicholas, 2015). Rather, the decision-analytical procedures have to account for the deep and dynamic uncertainties (for example by using the approach of many-objective robust decision making) (Hadka et al., 2015).

6. Open Research Questions

The discussion above reviews evidence for observed and projected changes in precipitation in Pennsylvania and how these changes link to flood hazards. There is a sizeable body of research that can already provide useful climate information. However, there are still many open research questions. Examples for these questions include:

1. What is the main driver of flooding in Pennsylvania?
2. What are the uncertainties surrounding the precipitation projections?
3. Which uncertainties related to precipitation projections (e.g., time-scale, percentile) are most decision-relevant?
4. What potential changes in observing systems, data analysis methods, and modeling techniques have the greatest potential for reducing these decision-relevant uncertainties?

Statement of author contribution

Klaus Keller, Robert Nicholas, and Mahkameh Zarekarizi devised and outlined the report. Mahkameh Zarekarizi wrote the initial draft. All three authors reviewed and edited the report.

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