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Economic Impacts of Atmospheric Rivers in the Transportation Sector: Methodology and Case Studies

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Aurora Project 2020-01

Final Report
May 2021

About Aurora

The Aurora program is a partnership of highway agencies that collaborate on research, development, and deployment of road weather information to improve the efficiency, safety, and reliability of surface transportation. The program is administered by the Center for Weather Impacts on Mobility and Safety (CWIMS), which is housed under the Institute for Transportation at Iowa State University. The mission of Aurora and its members is to seek to implement advanced road weather information systems (RWIS) that fully integrate state-of-the-art roadway and weather forecasting technologies with coordinated, multi-agency weather monitoring infrastructures.

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16. Abstract

Atmospheric rivers (ARs) are severe winter storms affecting the West Coast of the US. ARs decrease the safety of roadways, bringing heavy rainfall and winds, ice, and snow to the roads and increasing crashes, delays, and travel time.

This project included a literature review; developed a methodology to estimate the impacts of ARs on traffic, crashes, and road closures; applied the methodology to test sites in California, Colorado, and Utah; and estimated the direct costs of these impacts.

The California case study quantified the impacts of ARs on traffic volumes and vehicle miles traveled from 1996 to 2019 on I-5 from San Ysidro to the Oregon border.

The Colorado case study quantified the impacts of ARs on crashes, road closures, and delays during the severe avalanche month of March 2019 on 84 miles of I-70 west of Denver.

The Utah case study quantified the impacts of ARs on crashes, road closures, and delays from 2012 to 2019 at four sites: I-70 at Clear Creek Canyon, I-80 at Parley's Canyon, US 6 from Spanish Fork to Helper, and US 91 from Brigham City to Wellsville.

ARs were found to have significant impacts on crashes, road closures, delays, and traffic flows.

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Economic Impacts of Atmospheric Rivers in the Transportation Sector: Methodology and Case Studies

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EXECUTIVE SUMMARY

Background

Atmospheric rivers (ARs) are long, narrow features in the atmosphere that transport most of the water vapor outside of the tropics (Zhu and Newell 1998, Ralph et al. 2020). ARs are the largest “rivers” of freshwater on Earth, transporting on average more than double the flow of the Amazon River (AMS 2017). When ARs make landfall, or rise over mountainous terrain, the water vapor is released in the form of heavy rain or snow, which can have significant social and economic impacts (NOAA 2015). Like other forms of inclement weather, ARs can decrease the safety of roadways by bringing heavy rainfall, winds, ice, and snow and increasing crashes, road closures, delays, and travel time.

ARs have been shown to cause significant damage to property and infrastructure in the western US (e.g., Dominguez et al. 2018, Corringham et al. 2019, Vano et al. 2019). In the transportation sector, the U.S. Geological Survey (USGS) ARkStorm project (Porter et al. 2011) predicted the costs of a 1-in-1,000-year series of ARs to be $2.9 billion for road damage repair and reconstruction, $50 million for national freight network disruptions, and $23 million for business interruptions (all costs in 2021 dollars). A case study of a 2019 AR in California (Hatchett et al. 2020) estimated transportation costs of $21 million associated with slowdowns on I-5 and the closure of I-80.

These studies provide useful benchmarks for understanding an extreme worst-case scenario and the costs of a single impactful event. To date, there have been no comprehensive studies that quantify the costs of annual AR impacts on the road transportation system. This project developed a methodology to estimate the impacts of ARs on traffic, crashes, and road closures; applied the methodology to five test sites in California, Colorado, and Utah; and provided estimates of the direct costs of these impacts.

Objectives

The goal of this research was to develop a better understanding of the impacts of ARs on a number of road safety and mobility outcomes. The research objectives were as follows:

1. Develop a methodology that links data on AR occurrence and intensity to state department of transportation (DOT) traffic flow and road safety data
2. Develop statistical analyses to quantify the impacts of ARs on traffic flow and road safety outcomes
3. Quantify the impacts of AR occurrence and intensity on traffic flow rates over four sections of I-5 in California
4. Quantify the impacts of AR occurrence on traffic incidents, crashes, road closures, and delay times associated with road closures at five sites in Colorado and Utah
5. Quantify the economic costs associated with AR impacts at the case study locations

6. Propose ways in which operational AR forecasts of varying lead times could be used to mitigate the impacts of ARs on road transportation systems

Research Approach

The work documented in this report was conducted in four steps: (1) literature review; (2) acquisition and processing of AR and transportation data; (3) analysis of AR impacts, estimation of costs, and interpretation of the results; and (4) discussion of potential areas of future research.

The literature review included a number of studies on the impacts of adverse weather events on road safety and mobility, and cost estimation methods related to road transportation systems.

The AR and state DOT datasets are described and summarized. A set of spatially stratified multivariate regression analyses were executed to estimate the impacts of AR occurrence and intensity on the road safety and mobility outcomes of interest, controlling for confounding factors.

The statistical methods were applied to test sites in California, Colorado, and Utah. In California, the impacts of ARs on total flow rates on I-5 were quantified and translated into reductions in the economic value of vehicle miles traveled (VMT). In Colorado, the impacts of ARs on road closures on a section of I-70 west of Denver were quantified and translated into delay costs. In Utah, the impacts of ARs on crashes were quantified at four sites known to be impacted by adverse weather events. Following a discussion of the results and their limitations, possibilities for future research on ARs and the transportation sector were identified.

Summary of Project Findings

On I-5 over an 18 year period, ARs were associated with reductions in traffic flow from 2.5% in southern California to 6.8% in northern California. In absolute terms, total flow rates averaged over monitoring stations by region decreased by between 500 vehicles per day in northern California and up to 6,000 vehicles per day in southern California. The costs associated with these AR-related reductions in daily traffic flow were estimated at $106 million per year, with a possible range of $67 million to $467 million per year, depending on the assumed elasticity of road travel demand.

On an 84 mile section of I-70 west of Denver, during the significant avalanche month of March 2019, ARs increased the number of traffic events, spinouts, chain restrictions, full road closures, and closure durations. Crashes and traffic events decreased due to the closures and reduced flow rates, but the decreases were not statistically significant. Using observed traffic flow rates combined with closure durations, the delay costs to passenger vehicles and trucks associated with road closures were estimated to have exceeded $1.5 million over the corridor for the month.

Similar increases in the number and duration of road closures were associated with ARs at four sites in Utah from 2012 to 2019. Additionally, the number of crashes increased significantly during AR conditions. The costs of the AR-related increases in crashes were estimated to exceed $700,000 per year at the four sites.

Future Research

The methods developed in this study could be extended to estimate AR transportation impacts over wider geographic regions. Additional data on traffic flows could be used to improve the cost estimates of AR impacts on traffic volume, speed, delay, and travel time. Freight probe data combined with network modeling tools could be used to quantify the costs of ARs to freight transport networks. Broader economic costs of AR transportation impacts could be estimated as well, including those associated with reductions in demand for consumer goods in urban areas and reductions in tourist activities in mountain areas that depend on open and clear freeways for access.

An understanding of the impacts of ARs on road safety and mobility is critical to improved management of road systems during AR events. In recent years, there have been significant improvements in AR forecast technology with expanded observation networks and advances in dynamical modeling and machine learning capabilities. An operational AR transportation impacts index could be developed to enable transportation managers to better allocate resources during AR events and to mitigate against negative and costly outcomes. Further research could develop such tools and tailor them to the needs of transportation users and managers.

INTRODUCTION

Atmospheric Rivers

Atmospheric rivers (ARs) are narrow and lengthy dynamical structures that are responsible for the majority of horizontal water vapor transport outside of the tropics (Zhu and Newell 1998). They originate in the tropics via local moisture convergence (Bao et al. 2006) and form relatively narrow bands that stretch poleward. When these features make landfall, heavy and prolonged precipitation events can occur. Once an AR makes landfall, the presence of mountainous topography leads to the orographic ascent of air parcels, resulting in highly variable precipitation rates during an event. ARs contribute significantly to flooding and snowpack changes in western North America (Neiman et al. 2008).

The strongest events are often accompanied by anomalously warm temperatures, rain or snow, flooding, landslides, and debris flows (Neiman et al. 2008). Mountain ranges enhance lift, which dries out air masses and inhibits the downstream spread of moisture (Rutz et al. 2015). ARs that begin over the northern Pacific Ocean most often cause extreme precipitation over the Sierra Nevada and Cascade ranges but occasionally reach farther inland. A number of synoptic patterns are responsible for AR penetration into the northwest and southwest interior of the US (Rutz et al. 2014). When ARs pass through lowland corridors from the west, they are able to travel longer distances and generate extreme precipitation in the form of rain or snow throughout the intermountain western US (Rutz et al. 2014).

The economic impacts of ARs can be significant. A series of ARs following an anomalously wet period contributed to the failure of the emergency spillway at Lake Oroville dam in northern California in February 2017, resulting in repair costs in excess of $1 billion (Vano et al. 2019). In general, the economic costs of flooding due to ARs have been estimated at $1.1 billion per year over a 40 year period across the western 11 coterminous states (Corringham et al. 2019). In California, the U.S. Geological Survey (USGS) ARkStorm project estimated the total costs of a 1-in-1,000-year series of ARs to exceed $860 billion, almost one-third of California's annual state product (Porter et al. 2011).

Road Weather Impacts

Transportation is the lifeblood of the economy; the efficiency of the road transportation network is a fundamental contributor to economic growth (Sweet et al. 2014). Adverse weather events cause a number of impacts on the transportation system. Severe winter storms, hurricanes, and flooding can result in major stoppages or evacuations of transportation systems and cost millions of dollars. Day-to-day weather events such as high winds, rain, fog, snow, and freezing rain can have a serious impact on the mobility and safety of the transportation system users. These weather events result in increased fuel consumption, delay, and crashes and significantly impact the performance of the transportation system (Hranac et al. 2006).

The goals of transportation management include improving safety and mobility within road network systems. Weather events increase the variability of conditions faced in operations. With effective decision-support tools and sufficient data, weather events can be forecast with varying degrees of precision and accuracy, and their impacts can be predicted. Improved weather and impact predictions lead to improved operational response (Hranac et al. 2006).

Scope of Project

Weather impacts on road systems include the following:

- Stoppages, road closures, and evacuations
- Reduced flow rates, demand, speeds, and capacity
- Increased delays and travel times
- Canceled, postponed, and modified trips
- Increases in the number and severity of crashes and road safety incidents
- Increased maintenance, staffing, reconstruction, and recovery costs
- Freight delay, detour, and disruption costs
- Business disruption costs

This project focused on the impacts of ARs on road closures, flow rates, delays, and changes in the number and severity of road safety incidents. It did not consider maintenance costs, freight network impacts, or costs to the broader economy due to road network disruptions.

LITERATURE REVIEW

ARs in the United States

Atmospheric rivers (ARs) consist of narrow bands of enhanced water vapor transport at the boundaries of large areas of divergent surface air flow, including frontal zones associated with extratropical cyclones over the oceans (Zhu and Newell 1998, Ralph et al. 2020). In North America, ARs originating over the tropical Pacific Ocean travel toward western North America and make landfall from Baja California, Mexico to British Columbia, Canada. Atmospheric rivers are typically several thousand kilometers long and only a few hundred kilometers wide, and a single one can carry a greater flux of water than the Earth’s largest river, the Amazon River (AMS 2017). When ARs make landfall or are lifted over mountainous topography, they can bring sustained, heavy precipitation in the form of rain and snow and can sometimes cause extensive flooding and other adverse effects, often with severe economic consequences (Corringham et al. 2019).

Impacts of Adverse Weather on Road Transportation

An understanding of the impact of various weather conditions on roadside crash frequency and traffic intensity serves as an essential knowledge base for developing road management strategies. Wind speed impacts visibility distance due to blowing snow and dust and can cause lane obstruction due to wind-blown snow and debris, affecting traffic speed, travel time delay, and crash risk. Precipitation impacts visibility distance and pavement friction and can cause lane obstruction, affecting roadway capacity, traffic speed, travel time delay, and crash risk. Fog impacts visibility distance, affecting traffic speed, speed variance, travel time delay, and crash risk (FHWA 2020).

Adverse weather conditions cause important changes in travel decisions: mode, departure time, and route diversions. Adverse weather increases operating and maintenance costs of winter road maintenance agencies, traffic management agencies, emergency management agencies, law enforcement agencies, and commercial vehicle operators. Winter road maintenance accounts for roughly 20% of state DOT maintenance budgets. Each year, state and local agencies spend more than $2.3 billion on snow and ice control operations (FHWA 2021).

Shi and Fu (2018) presented an edited collection of studies on sustainable winter road operations, including work on the safety and mobility effects of winter weather and road maintenance and the economic benefits of winter road operations.

Lawrence et al. (2014) provided a primer on a road weather benefit-cost analysis. They identified a number of costs to users associated with adverse weather, including travel time and delay, reliability, crashes, and vehicle operating costs. Costs to agencies include design and engineering, land acquisition, construction, reconstruction and rehabilitation, preservation, routine maintenance, and mitigation.

IHS Global Insight (2010) estimated the broader economic costs of road transportation disruptions from a snowstorm in the northeastern US and Canada to be on the order of $300 to $700 million for a single-day event, that is, roughly $360 to $845 million in 2021 dollars.

Motor Vehicle Crashes

The Federal Highway Administration (FHWA) reported 5,891,000 vehicle crashes annually over the period of 2007 to 2016. One-fifth (21%) of these crashes were weather-related, where weather-related crashes are defined as those crashes that occur in adverse weather (i.e., rain, sleet, snow, fog, severe crosswinds, or blowing snow/sand/debris) or on slick pavement (i.e., wet pavement, snowy/slushy pavement, or icy pavement). Annually, 5,000 people are killed, and more than 418,000 people are injured in weather-related crashes. The majority of weather-related crashes occur on wet pavement (70%) and during rainfall (46%). A smaller percentage occur during winter conditions: 18% during snow or sleet, 13% on icy pavement, and 16% on snowy or slushy pavement; in addition, 3% of weather-related crashes occur in the presence of fog.

Blincoe et al. (2015) quantified the economic and societal impact of motor vehicle crashes across the US. They noted that in 2010, there were 32,999 people killed, 3.9 million people injured, and 24 million vehicles damaged in motor vehicle crashes in the US. They estimated the economic costs of these crashes to be $242 billion in 2010 dollars, 1.6% of the $14.96 trillion real US gross domestic product for 2010. Of this total, medical costs were responsible for $23.4 billion, property damage losses for $76.1 billion, lost productivity (both market and household) for $77.4 billion, and congestion impacts for $28 billion. All other crash-related costs totaled $37 billion. In 2021 dollars, the total cost amounts to approximately $292 billion, a 20% increase over 2010 dollars; component costs scale proportionally.

More recently, Harmon et al. (2018) estimated crash costs for highway safety analysis. They provided updated per person injury costs and per vehicle property damage associated with motor vehicle crashes. They also provided a comprehensive literature review of crash cost studies.

Maze et al. (2005) investigated the impacts of weather-related crashes on I-35 in northern rural Iowa from 1996 to 2000. They found that winter weather conditions were associated with 21% of all crashes over the study period but that crash severity and average loss per crash are lower when related to winter weather.

The National Research Council (2004) provided a research agenda for improving road weather services. They reported that adverse weather and weather-related degradation of road conditions were associated with over 1.5 million vehicular crashes per year, which resulted in 800,000 injuries and 7,000 fatalities annually. The injuries, loss of life, and property damage from weather-related crashes cost an average of $64 billion annually (Lombardo 2000) in 2021 dollars.

Mobility Impacts

Capacity reductions can be caused by lane obstruction due to flooding, snow accumulation, and wind-blown debris. Road closures and restrictions due to hazardous conditions also decrease roadway capacity. Light rain can decrease freeway capacity by 4% to 11%, and heavy rain can cause capacity reductions of 10% to 30%. Capacity can be reduced by 12% to 27% in heavy snow and by 12% in low visibility (FHWA 2020).

Weather events reduce mobility. On arterial routes and freeways, speed reductions due to adverse weather events range from 10% to 25% on wet pavement, from 30% to 40% on snowy or slushy pavement, and from 3% to 16% in light rain or snow. Heavy rain decreases average speed by 3% to 16%; heavy snow decreases speed by 5% to 40%. Low visibility reduces speed by 10% to 12%. Free-flow speeds are reduced by 2% to 17% in rain and by 5% to 64% in snow. Traffic volumes decrease by 15% to 30%, saturation flow rates decrease by 2% to 21%, and travel time delay increases by 11% to 50% in adverse weather conditions (FHWA 2020).

At the network level, adverse weather events increase the uncertainty in system performance, resulting in a network capacity reduction ranging from 10% to 20% in heavy rain for instance (De Palma and Rochat 1999). Day-to-day weather conditions such as fog and precipitation can reduce travel, e.g., drivers postpone or cancel discretionary activities, but can also have an increased effect on traffic when travel modes are shifted from slow modes (walking, cycling) toward motorized vehicles (Hranac et al. 2006).

Afrin and Yodo (2020) surveyed traffic congestion measures and noted that adverse weather can affect traffic flow and driver behavior. They considered impacts on a number of metrics including speed reduction index (SRI), speed performance index (SPI), travel rate, delay ratio, delay rate, volume-to-capacity (V/C) ratio, relative congestion index, congested hours, travel time index, and planning time index. They presented a case study applying these metrics to one week of traffic data in Chicago, Illinois in 2018.

Agarwal et al. (2005) considered the impacts of light rain, heavy rain, light snow, and heavy snow on urban freeway traffic flow and capacity in the Minneapolis–Saint Paul, Minnesota metropolitan area from 2000 to 2004. They found that adverse weather reduced capacity and operating speeds with the greatest impacts from heavy snow events.

Akin et al. (2011) considered the impacts of weather on traffic flow across two highway bridges in Istanbul in 2009, providing a number of assessments of speed-density-volume relationships. They found that rain reduced speeds by 8% to 12% and reduced capacity by 7% to 8%.

Blattenberger and Fowles (1995) presented a model of road closure and avalanche danger applied in a case study of Little Cottonwood Canyon in northern Utah. Their focus was on evaluating the costs and benefits of road closures to mitigate avalanche damages. They estimated road closure costs to ski resorts in the 1991–1992 season to be approximately $2.4 million per day in 2021 dollars.

Chin et al. (2004) considered temporary losses of highway capacity and their impacts on road network performance at the national level in 1999. They included an analysis of weather impacts in which they estimated normal delay times and delay times during adverse weather conditions. They also estimated capacity losses and delay times. They found that weather events accounted for 9% of lost time due to delays, which they valued at approximately $7.8 billion in 2021 dollars.

Clydesdale (2000) quantified the economic impact of road closures caused by natural hazards in New Zealand's Kaikoura District and found disruption costs of over $220,000 in 2021 US dollars associated with increased travel time costs and vehicle operating costs.

Cools et al. (2009) assessed the impact of temperature, sunshine, precipitation, hail, snow, and thunderstorms on traffic intensity in Belgium at three urban locations in 2003 and 2004. They noted that traffic intensity is a primary determinant of traffic safety and that injury crashes are proportionally related with exposure. They found that inclement weather decreased traffic intensity while higher temperatures and sunshine increased traffic intensity.

Dalziell and Nicholson (2001) investigated the impacts of snow and ice, volcanic eruptions and lahars, earthquakes, and traffic crashes on road closures and road closure costs on the Desert Road section of New Zealand's State Highway 1. They modeled the effects of road closures on traffic flow using a traffic assignment model with and without allowing for the elasticity of travel demand. They estimated annual costs of road closures due to snow and ice at over $1.5 million in 2021 US dollars. They also assessed the costs and benefits of mitigation options for reducing the risk of road closure.

Hallenbeck et al. (2014) estimated the travel costs associated with flood closures of state highways near Centralia and Chehalis, Washington using the INRIX travel time database and a survey of motorists. They estimated the costs of a 100 year flood to be on the order of $13.3 million, due to a 5 day closure of I-5. The costs included $9.4 million in additional time and mileage associated with detours and $1.8 million in costs associated with abandoned trips (all costs in 2021 dollars).

Mallela and Sadasivam (2011) estimated costs associated with work zones, some of which were related to adverse weather. They included methods on calculating travel delay costs, vehicle operating costs, crash costs, emission costs, network impacts, and non-monetary and qualitative impacts. Their final report included a number of useful cost parameters provided in tables.

Maze et al. (2005) investigated the impacts of weather on traffic demand, traffic safety, and traffic flow on I-35 in northern rural Iowa from 1996 to 2000. They found that rain reduced capacity by 2% to 14% and speeds from 2% to 6%, depending on intensity. Snow had the greatest impacts, reducing capacity by 4% to 22% and speeds by 4% to 13%. Low temperatures reduced capacity by 1% to 8% and speeds by 1% to 2%. High winds reduced capacity and speeds by 1%. Low visibility due to fog reduced capacity by 10% to 12% and speeds by 7% to 12%.

The Oregon Department of Transportation (DOT) (2019) estimated the hourly costs of unexpected delay and increases in travel times for vehicles in Oregon in 2017. The method combined value-of-time estimates with data from automatic traffic recorders. Value-of-time estimates are derived from household income and compensation data, national average vehicle occupancy rates, and estimates of the share of trips taken for business purposes.

Peng et al. (2018) used analysis of variance (ANOVA) and logistic regression methods to quantify the effects of rain and fog on mean headway distance, the standard deviation of speed, and the standard deviation of headway distance. They considered a test site on I-4 in Polk County, Florida from 2007 to 2009. They found that both rain and fog increased mean headway distance, and increased variability in speeds and headway distance, with greater impacts for rain.

The National Research Council (2004) study reported that heavy rain and wet pavement conditions led to speed reductions of 25% and decreases in road capacity of 10%. Snow events led to speed reductions of 40% and capacity reductions of 25% to 30%. Low visibility caused drivers to reduce their speed by 15% to 40%. Delays on highways and principal arterial roads due to fog, snow, and ice were estimated to exceed 500 million hours.

Road Freight Networks

Trucking companies or commercial vehicle operators lose an estimated 32.6 billion vehicle hours annually due to weather-related congestion in 281 of the nation's metropolitan areas. Nearly 12% of total estimated truck delay is due to weather in the 20 cities with the greatest volume of truck traffic. The estimated cost of weather-related delay to trucking companies ranges from $3.2 billion to $5.1 billion annually (Maccubbin 2002) in 2021 dollars.

Mesa-Arango et al. (2013, 2016) estimated the economic impacts of disruptions to intermodal freight systems traffic associated with 2008 northwestern Indiana floods, using the Freight Analysis Framework version 3 (FAF3). They estimated total economic loss from the delay of shipments of commodities in the study region to be 60 fewer jobs, $12.3 million in sales, $3.7 million in labor income, $1.3 million in taxes, and $6.0 million in value added, in 2021 dollars.

Krechmer et al. (2012) estimated weather delay costs to trucking and regional weather impacts on freight. They considered the impacts of rain, snow, thunderstorm, hail, and fog at the national level using the Highway Performance Monitoring System and a number of freight data sources including the FHWA's FAF. They estimated weather-related delay costs to the road freight industry to be on the order of $9 to $10 billion in 2021 dollars.

In a follow-up paper, Krechmer et al. (2016) conducted a regional analysis using similar methods and found that ice and snow events were associated with half of all lost time due to weather-related decreases in traffic speed, with associated costs of $27 per segment hour and $0.27 per truck per segment in 2021 dollars.

Transportation Agency Costs

Weather-related costs are also incurred by state and local agencies that maintain and operate roadways. More than $2.8 billion is spent annually on snow and ice control operations and over $7.1 billion annually on infrastructure repair due to ice and snow damage, in 2021 dollars. Winter road maintenance accounts for 20% of state maintenance budgets (FHWA 2020).

Venner and Zamurs (2012) surveyed the increasing maintenance costs to DOTs associated with extreme weather events and climate change. Specifically, they considered the impacts of climate change on heat, forest fires, wind and dust storms, intense precipitation, flooding, and winter storms. They presented a range of short-term and long-term mitigation strategies for road management agencies.

RESEARCH METHODOLOGY

Overview

The research methodology included the following steps:

1. Combine data on AR location and intensity with road safety and mobility data from state DOTs
2. Calculate the impacts of ARs on crashes, road closures, delays, and traffic flows
3. Estimate the costs of the AR road safety and mobility impacts

AR Data

AR data were obtained from two sources. ARs are typically defined in terms of a combination of geometric constraints and above-threshold levels of integrated vapor transport (IVT). There are a number of AR detection algorithms (Shields et al. 2018). In this study, two catalogs based on work by Guan and Waliser (2015, 2017, 2019) and Guan et al. (2018) were used.

The first catalog provides the occurrence of ARs at specific locations across the US. The second, more recent catalog also provides IVT values at each grid cell, which allows for analyses of the effects of AR intensity on road safety and mobility outcomes.

The first catalog applies the Guan and Waliser (2015) AR detection algorithm to Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) reanalysis data. The second applies an updated AR detection algorithm, the Guan and Waliser (2019) version 3 Tracking Atmospheric Rivers Globally as Elongated Targets (tARget) algorithm. The Guan and Waliser (2019) catalogue was developed for the period between 1979 and 2019 using six-hourly instantaneous fields of global IVT at 1.5° resolution from the ERA-Interim reanalysis (Dee et al. 2011).

MERRA-2 is a weather reanalysis product developed by National Aeronautics and Space Administration's (NASA's) Global Modeling and Assimilation Office (GMAO) that assimilates a wide range of weather data sources and spans the satellite observing era of 1980 to the present. The spatial resolution of MERRA-2 is 0.625° longitude × 0.5° latitude. Details on the dataset can be found in Gelaro et al. (2017).

ERA-Interim is a weather reanalysis product developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) that assimilates a wide range of weather data sources and covers the period of January 1, 1979 to August 31, 2019. The spatial resolution of ERA-Interim is approximately 0.7°. It has been superseded by the ERA5 reanalysis. Details on the dataset can be found in Dee et al. (2011).

The availability of IVT levels associated with ARs allows for the application of the Ralph et al. (2019) AR ranking scale (Figure 1).

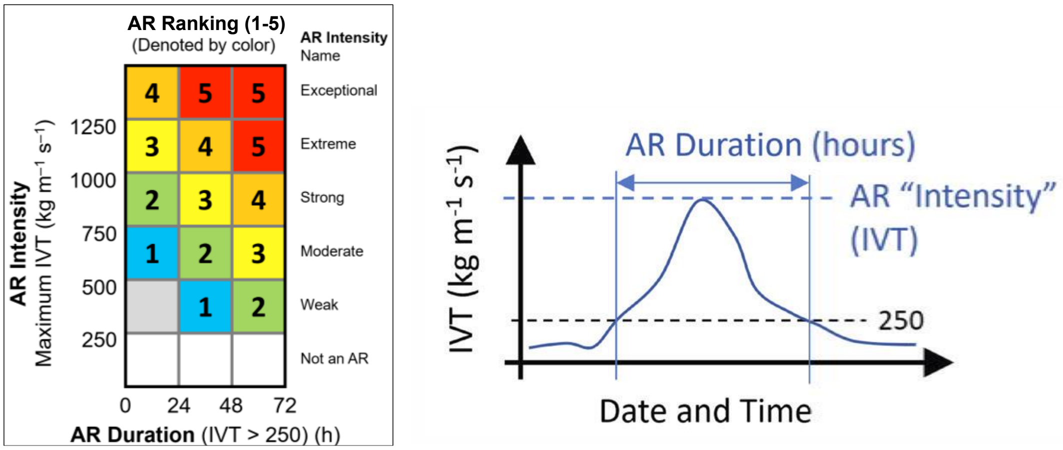

Figure 1. Ralph AR ranking scale

The AR scale ranks ARs on a scale of 1 to 5 based on AR duration and intensity as measured in terms of IVT. ARs are defined according to one of several detection algorithms and then classified based on peak IVT at a given timestep. If IVT exceeds 250 kg m^{-1} s^{-1} and duration is between 24 and 48 hours, then the AR is classified as an AR1 storm. With each increase in IVT of 250 kg m^{-1} s^{-1}, the rank of the AR is increased up to a maximum of AR5. Additionally, if the duration of the AR is less than 24 hours, then the AR is demoted in rank by one level. If the duration is greater than 48 hours, then the AR is promoted in rank by one level.

There are several ways in which the ranking algorithm can be applied, including over the entire event or at a specific location. Here, the algorithm is applied at specific locations. A grid cell with maximum IVT over the course of the AR of 600 kg m^{-1} s^{-1} for which the AR is present for 60 hours would be classified as an AR4 event. Were an AR with the same peak IVT to persist for only 36 hours over the same location, it would be classified as an AR3 event.

State DOT Data

Caltrans PeMS V-Class Traffic Flow

Data on traffic volumes were extracted from the California DOT (Caltrans) freeway Performance Measuring System (PeMS). Descriptions of the data can be found in Chao (2003), and Kwon et al. (2007). More extensive documentation is available at the PeMS website: pems.dot.ca.gov.

The main PeMS dataset used in the traffic flow analysis was the Census V-Class Day dataset. The dataset covers the period of January 1, 1996 to December 31, 2012 and consists of observations taken from 94 census substations on I-5 from absolute postmile 42.5 to 795.6. The dataset includes 173,116 observations, of which 107,479 had positive values for total flow. Flow rates were also reported for specific vehicle classes from motorcycles and passenger cars to light trucks and heavy trucks with a number of different configurations.

The data were linked to a separate dataset containing the latitude and longitude of I-5 postmiles in order to locate the census substations to the nearest AR grid cell.

The California V-class daily total flow data were divided into four regions: southern California defined as latitude less than 34.75°N, central California between 34.75°N and 37.25°N, Bay Area between 37.25°N and 39.75°N, and northern California north of 39.75°N.

Additionally, data on vehicle miles traveled (VMT) were obtained from PeMS Performance Aggregates datasets for I-5 in both directions from postmiles 0 to 525 over the time period of January 1, 2010 to December 31, 2019. The VMT data were used to estimate the economic impacts of ARs on mobility.

Colorado DOT Incidents and Traffic Flow

Colorado DOT (CDOT) incident data consisted of location descriptors (road, direction, location, and mile marker start and end), the event start and end dates and times, event type (chain law, event response, incident, and weather event), event sub class (24 values, including descriptions of whether the event affected a single vehicle, multiple vehicles, or all vehicles), a measure of severity (minimal, moderate, or severe), and durations of partial and total freeway closures. The I-70 data were obtained from CDOT on April 3, 2020.

Utah DOT Incidents

Utah DOT incident data consisted of location descriptors (main street, cross street, direction, latitude, and longitude), a description of the event (i.e., web description), the date and time that each incident report was created, and the date and time that each incident report was last updated. Two fields indicating the incident type were provided, one describing the incident with text and the other coded from a set of 16 types. A measure of impact was provided on a scale of 0 to 10. A second description field was also provided that included information on crash severity, priority, and impact. Severity was rated high, medium, low, or none. Priority was ranked on a scale of 1 to 10.

An example of the web description field is “Vehicle Fire I-80 AT MP 131 CLEARED AT 11:37 AM.” The field contains information on the nature and location of the incident and the time the incident was cleared. Various items were extracted from the web description field. Simple text searches extracted information on partial and full closures, e.g., “Crash I-80 AT MP 133 LEFT LANE CLOSED CLEARED AT 11:35 PM” was classified as a partial lane closure, and “I-80 CLOSED MP 130 USE ALT ROUTE” was classified as a full closure.

Duration of incidents, including road closures, were calculated in minutes as the difference between the date and time at which the incident report was created and the date and time at which the incident report was last updated.

The I-80 data consisted of 2,244 incidents from October 10, 2012 to December 31, 2019 from milepost 129 to 141. The I-70 data consisted of 219 incidents from December 17, 2012 to December 31, 2019 from milepost 0 to 23. The US 6 data consisted of 1,094 incidents from October 14, 2012 to December 31, 2019 from milepost 179 to 230. The US 91 data consisted of 208 incidents from February 5, 2014 to December 31, 2019 from milepost 4 to 16. The I-80 data were obtained from the Utah DOT on March 31, 2020, and the data on the remaining sites were obtained on December 29, 2020.

Linking AR Data to Transportation Data

For California and Colorado, only the milepost locations of census substations and incidents were given. Latitude and longitude were applied to mileposts by matching to a U.S. Census Bureau dataset providing the locations of the mileposts. The California and Colorado data were then matched to nearest AR grid cell. The Utah incident data provided the latitude and longitude of each event directly. This location information was used to link the incident data to the nearest AR grid cells.

Temporally, the AR data were aggregated from six-hourly resolution to the daily level. In this way, a given location-day was classified as an AR day or a non-AR day using the Guan and Waliser (2015) MERRA-2 dataset. In the Colorado and Utah data, all AR grid cells nearest to any milepost in the study region were spatially aggregated. If any of the grid cells on a given day was classified as an AR day, then that day was classified as an AR day for that study site. All incidents at any of the Colorado or Utah sites were then classified as AR or non-AR incidents. These classifications were used to build models and test hypotheses about the impacts of ARs on road safety and mobility.

In the California analysis, the AR data were processed in the same way, but additionally the data were classified according to the Ralph et al. (2019) AR ranking system using the Guan and Waliser (2019) ERA-Interim data that also contained IVT magnitudes. In this way, all traffic flow observations in each section of I-5 were classified as AR or non-AR traffic flow rates, and as AR1 through AR5 traffic flow rates.

Methodology

California Costs of Reduced Mobility

A multivariate linear regression approach was used to quantify the impacts of AR conditions on road safety and mobility. In California, the dependent variable was I-5 traffic flow in vehicles per day over four regions (southern California, central California, Bay Area, and northern California). The independent variable for each geographic location was the occurrence of AR conditions in addition to control variables including the direction of traffic (north or south), the day of the week, and whether the day was a holiday. An additional analysis was conducted in which the independent variable was a categorical variable indicating the ranking of the AR, with a reference value of "no AR" for non-AR days.

To estimate costs associated with reduced flow rates, daily VMT at each census substation were estimated as a function of regional AR occurrence, controlling for day of week and holiday effects using separate regression models for each census substation. From these models, the impacts of ARs on VMT at each census substation were estimated. These VMT impacts were then aggregated over census substations by region. Baseline estimates of VMT for each census substation were also estimated over the 1996 to 2016 period. From the baseline VMT and the AR effect on VMT, it was possible to calculate the percent change in VMT associated with ARs for each region.

Several assumptions were made in order to estimate the economic impacts of reduced flow rates. Gillingham (2014) estimated the elasticity of VMT for passenger vehicles with respect to the price of gasoline to be -0.22. That is, a 1% increase in the price of gasoline is associated with a 0.22% decrease in VMT.

The cost of gasoline is one component of vehicle operating costs, which also include maintenance and repair costs, tires, and mileage-dependent depreciation. Mesa-Arango et al. (2013) reported vehicle operating costs of 29.04 cents per mile, in 2021 dollars, for passenger cars and vans, of which gasoline costs account for 9.48 cents per mile. Another element of the cost of a VMT is the value of time. Mesa-Arango et al. (2013) report an average value of $27.07 per hour for passenger cars, in 2021 dollars. Assuming an average driving speed of 60 miles per hour on I-5, this translates into a cost of 44.9 cents per mile. Hence, the total cost of a VMT for passenger vehicles is estimated to be 73.9 cents per mile.

It is assumed that VMT are of value to vehicle operators, i.e., trips will be taken when the value of or willingness to pay for a given number of VMT exceeds the cost. Assuming that the cost components of each element of VMT are additively separable and assuming a linear demand curve with an elasticity of demand of -0.22 at the equilibrium price and quantity of VMT, it is possible to specify the relationship between the demand, or willingness to pay, for an additional VMT and the total number of VMT observed in a given region over a given time period. The area below the demand curve but above the known VMT cost is the consumer surplus, i.e., the value of VMT to travelers (Boardman et al. 2018). The reduction in consumer surplus due to reduced VMT demand under AR conditions is used as the estimate of the cost to road users of decreased mobility due to AR conditions.

Colorado Costs of Delay Times Due to Road Closures

In Colorado, a number of outcomes are modeled as a function of the incidence of AR conditions: the number of events; the number of chain restrictions; the duration of events; the number of spinouts; the number of partial and full road closures; the number of minimal, moderate, and severe events; the number of incidents; the number of crashes; the number of debris events; the number of traffic events; the duration of partial and full road closures; and the number of hour-miles closed. Day-of-week controls are included in the model.

Hourly traffic volumes were obtained from the CDOT Online Transportation Information System (OTIS) for the month of March 2019 over six monitoring stations in both freeway directions. Hourly vehicle flow rates in each direction were matched to the road closure times and durations. A sample of 744 hours (31 days times 24 hours) was created in which average hourly flow rates over the domain were linked to the number of minutes of road closures observed that hour. A set of regressions were then used to estimate the impact of road closures on vehicle hours of delay, controlling for the time of day. In this way, the flow reductions associated with eastbound, westbound, and full closures were estimated.

Using estimates of delay costs for passenger vehicles and commercial trucks (Ellis 2017) combined with average annual daily traffic (AADT) counts to estimate the fraction of vehicles in each class, the costs of the estimated additional vehicle hours of delay associated with AR conditions were calculated.

Utah Costs of Crashes

In Utah, the following outcomes were modeled as a function of the incidence of AR conditions, controlling for day of week and holiday effects: the number of events, the number of crashes, the number of partial and full closures, the cumulative impact rating events over the course of a day, and the duration of each event.

For crashes, cost estimates were calculated using crash cost statistics from Blincoe et al. (2015), who broke down crash costs by property damage and injury costs for injuries of varying severity. Assuming that the distributions of injury severity, number of cars involved in crashes, and number of injuries per crash at each site were equal to the distributions presented in Blincoe et al. (2015), the total damage plus injury cost of each crash was estimated at $21,500 in 2021 dollars. AR-related crash costs were obtained by applying this estimate to the estimated increases in crashes associated with AR days for each site.

CASE STUDY: I-5 IN CALIFORNIA

The main arterial north-south route in the California road network is I-5, which extends from the Mexican border at San Ysidro in San Diego, California to the Oregon border at Hilt, California.

California road networks and the MERRA-2 data grid for ARs are shown on the left in in Figure 2. Gray cells indicate the 0.5° latitude by 0.625° longitude cells over which ARs are defined. Line segments indicate different types of highways in California. I-5 is shown on the right in Figure 2, divided into four regions for analysis, named northern California, Bay Area, central California, and southern California. Additionally, the figure on the right shows the MERRA-2 grid cells used for AR occurrence analysis compared to the ERA-Interim grid cells used for AR intensity and AR ranking analyses.

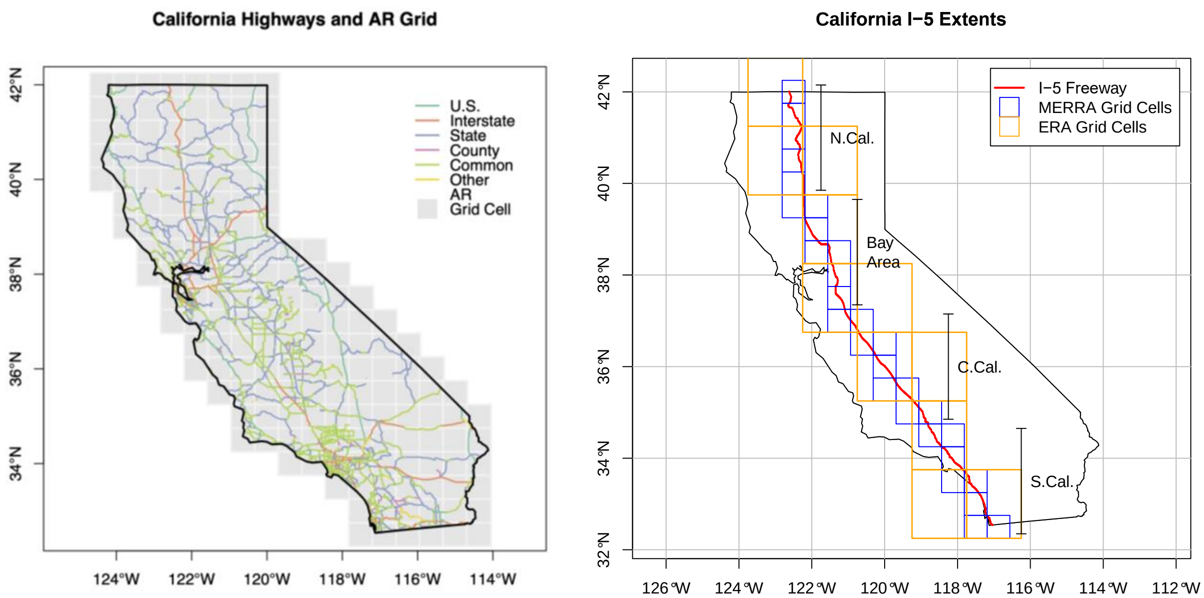

Figure 2. California road network, AR grid cells, and study regions

The effects of ARs on V-class traffic flows obtained from the Caltrans PeMS database are shown in Table 1.

Table 1. Impacts of ARs on I-5 V-class flows

Section	Mean flow	AR effect	% AR effect	p-value	% AR days
All ARs					
Northern California	14,581	-735	-5.0	2.5×10^{-55} ***	21.1
Bay Area	16,297	-621	-3.8	2.2×10^{-48} ***	19.6
Central California	18,514	-563	-3.0	2.0×10^{-6} ***	19.5
Southern California	107,490	-2,702	-2.5	2.3×10^{-27} ***	17.7
Moderate to Strong ARs					
Northern California	14,581	-796	-5.5	4.6×10^{-41} ***	11.9
Bay Area	16,297	-711	-4.4	1.5×10^{-38} ***	10.7
Central California	18,514	-906	-4.9	1.8×10^{-9} ***	9.6
Southern California	107,490	-3,702	-3.4	1.2×10^{-31} ***	8.2
Strong ARs					
Northern California	14,581	-771	-5.3	2.2×10^{-23} ***	6.6
Bay Area	16,297	-615	-3.8	2.7×10^{-18} ***	6.2
Central California	18,514	-1,184	-6.4	4.4×10^{-9} ***	5.1
Southern California	107,490	-6,191	-5.8	5.1×10^{-46} ***	4.1

Significance: *** p <0.001 on linear regression controlling for location, day of week, and holidays. AR conditions: at least one six-hour period with AR conditions in the spatial grid cells, which cover the road extent on the day in question, using the Guan and Waliser (2015) MERRA-2 AR detection algorithm. Moderate-to-Strong AR: at least half the grid cell time periods are associated with AR conditions. Strong AR: at least three-quarters of the grid cell time periods are associated with AR conditions.

AR conditions were found to reduce traffic flows by 5% in northern California, 3.8% in the Bay Area, 3% in central California, and 2.5% in southern California. In absolute terms, the reductions were greatest in southern California, with a reduction in flow of 3,700 vehicles per hour from a baseline of 107,000.

To reduce the proportion of days considered to be AR days, more stringent requirements were imposed, namely, days where at least half of the grid cell time periods were detected as ARs were classified as moderate AR days, and days where at least three-quarters of grid cell time periods were detected ARs were classified as strong AR days. Traffic flow rates generally decrease as AR intensity increases, though slight increases in flow rates were observed for strong ARs relative to moderate-to-strong ARs in northern California and the Bay Area. This is likely due to noise in the data. Under strong AR conditions, reductions were on the order of 4% to 6% across the different regions, or 600 to 6,000 vehicles per hour. It should be noted that these AR classifications were ad-hoc classifications based on the available fields in the MERRA-2 AR detection product. Additional analyses of the impacts of AR intensity on traffic flows are presented below using the ERA-Interim IVT data to classify ARs according to the Ralph et al. (2019) ranking system.

As an alternative to considering the Guan and Waliser (2015) MERRA-2 numbers of grid cell time periods as a measure of AR intensity, an additional analysis was performed using ERA-Interim IVT data associated with the Guan and Waliser (2019) detection algorithm. The ERA-Interim data are projected over a larger spatial grid (1.5° instead of 0.5° by 0.625° in the MERRA-2 reanalysis) but have the advantage of allowing for the classification of ARs using the 1 to 5 AR ranking scale. As described in the Research Methodology chapter, the scale (shown previously in Figure 1) categorizes ARs based on peak IVT in increments of 250 kg m^{-1} s^{-1} and then adjusts the category based on the duration of the event. Effects of ARs by rank range from mostly beneficial, e.g., replenishing the water supply (categories 1 and 2: short duration, low IVT), to mostly damaging (categories 4 and 5: long duration, high IVT).

The results (Figure 3) are largely as expected. Notably, the reductions in average traffic flow rates across monitoring stations range from 7% to 18% under extreme AR4 and exceptional AR5 conditions.

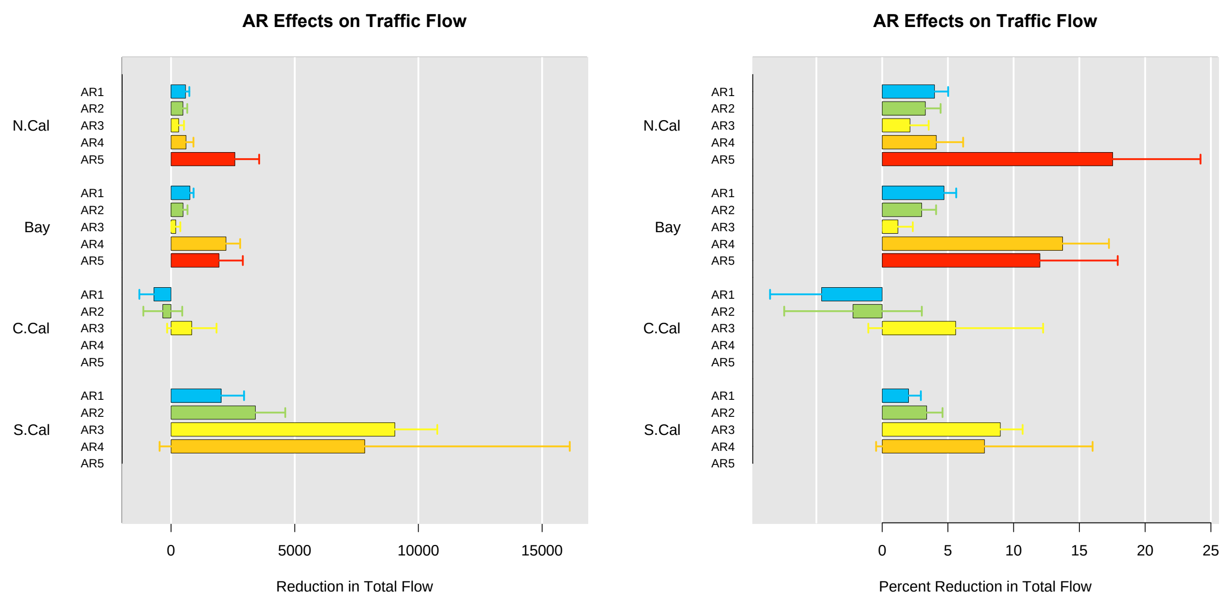

Figure 3. Impacts of ARs on I-5 V-class flows by AR ranking

The decreases in traffic flow are not monotonic with increases in AR scale in northern California, the Bay Area, or southern California, although the general trend is as expected. In addition, AR1 and AR2 storms are associated with increased traffic flow in central California, though the increases are not statistically significant. The central California section of I-5 is located farther inland in the Central Valley, on the leeward side of the Southern Coast Ranges, where AR impacts are less intense than on the windward side of the Coast Ranges or on the windward side of the Sierra Nevada Range to the east. This may explain this result.

Finally, the greatest impact in terms of reduced traffic flow occurs in northern California during AR5 events. AR activity is known to be most intense in northern California, so this result is consistent with expectations.

In order to calculate costs associated with mobility reductions due to ARs, it is simpler to work with VMT as these can be consistently aggregated over monitoring stations to the regional level (Chao 2003). Daily VMT values were obtained from PeMS Performance Aggregates Time Series from January 1, 2010 to December 31, 2019 over specified sections of I-5 (north and south combined): southern California postmiles 0 to 197, central California postmiles 197 to 417, and Bay Area postmiles 417 to 525 (Table 2). VMT values were not available from PeMS on the I-5 north of the postmile 525 crossing, so the region of northern California was excluded from the cost analysis.

Table 2. Impacts of ARs on I-5 V-class VMT

Region	Mean daily VMT	AR effect on daily VMT	% effect of AR on VMT	Annual change in consumer surplus due to ARs (millions $)
Southern California	30,331,000	-370,000	-1.22	80.5
Central California	4,607,000	-64,000	-1.40	14.0
Bay Area	4,027,000	-53,000	-1.31	11.4
All I-5	38,965,000	-487,000	-1.25	105.9

For each region, VMT regressed on an indicator variable for AR conditions in that region, day of week, and holiday effects. Using a linear demand curve estimated using VMT costs of $0.73 per mile in 2021 dollars (adapted from Mesa-Arango et al. 2013) and an assumed VMT demand elasticity of -0.22 (Gillingham 2014), the baseline (non-AR day) VMT per region were combined with the change in VMT due to ARs to calculate the associated change in consumer surplus.

A VMT demand curve (Figure 4) represents the quantity of VMT demanded at any given price of VMT.

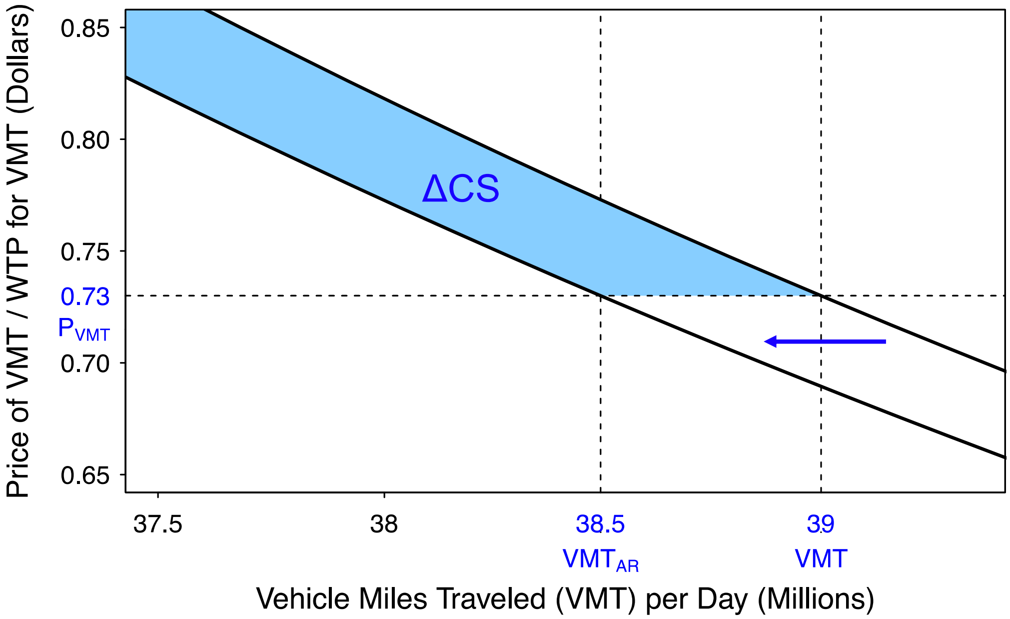

Figure 4. Change in I-5 consumer surplus due to AR conditions

The demand curve represents the willingness of vehicle operators to pay for each additional mile traveled. For low quantities of VMT, consumers are willing to pay high prices; for high quantities, consumers are willing to pay lower prices for additional VMT. The difference between the willingness to pay for a given number of VMT and its price is the consumer surplus, or the welfare gain to vehicle operators associated with that VMT (Boardman et al. 2018). For a fixed price, the consumer surplus or welfare to consumers of VMT is represented as the area under the demand curve above the price level.

AR conditions decrease observed VMT in all regions. This is represented graphically by a leftward shift in the demand curve: at any hypothetical price of VMT, vehicle operators will choose fewer VMT during AR conditions. The change in the area under the demand curve and above the price is shaded light blue and represents the loss of consumer surplus to vehicle operators associated with AR conditions.

Daily changes in consumer surplus were calculated for each region and then summed to generate a total cost over I-5 from postmile 0 to 525. The values were then multiplied by the number of AR days in each region to obtain annual costs of AR conditions in terms of reduced VMT consumer surplus. The Gillingham (2014) VMT demand elasticity of -0.22 applied at the mean daily VMT of 38.5 million and the Mesa-Arango et al. (2013) VMT price of $0.73 per mile were used to generate a linear demand function, which was then shifted based on the estimated effect of AR conditions on VMT. This yielded an estimate of the annual cost of ARs in terms of reduced consumer surplus of $106 million.

The demand elasticity of -0.22 is one of several that have been estimated in the literature. Litman (2019) presented a range of road travel demand elasticities from a number of different studies.

To consider the sensitivity of the estimate of annual AR costs to vehicle operators on I-5 in terms of reduced VMT, the calculations were repeated over a range of elasticities from -0.35 to -0.05. The results generated a range of AR cost estimates from $67 million to $467 million per year, corresponding to demand elasticities of -0.35 to -0.05, respectively (Table 3).

Table 3. Annual reduction in consumer surplus due to AR conditions (millions $)

Elasticity	Southern California	Central California	Bay Area	I-5
-0.35	51	9	7	67
-0.30	59	10	8	78
-0.25	71	12	10	93
-0.20	88	15	13	116
-0.15	118	20	17	155
-0.10	177	31	25	233
-0.05	354	62	50	466

VMT demand elasticities in the literature are typically calculated with respect to fuel price changes, which make up a small component of the total cost of VMT (between 10% and 20% of the total cost). Calculating a VMT demand elasticity with respect to total VMT costs, including the implicit costs of inclement weather, is a potential area for future research. It is expected, however, that such an estimated elasticity would fall within the range presented above in Table 3.

CASE STUDY: I-70 IN COLORADO

Colorado road networks and the data grid for ARs are shown in Figure 5. Grid cells over which ARs are defined are indicated in gray. The highway network in Colorado is indicated as a set of light blue line segments. I-70 is indicated in pink, with the section of interest (mile marker 156 to 240) in red. The five AR grid cells that intersect this section of I-70 are outlined in green.

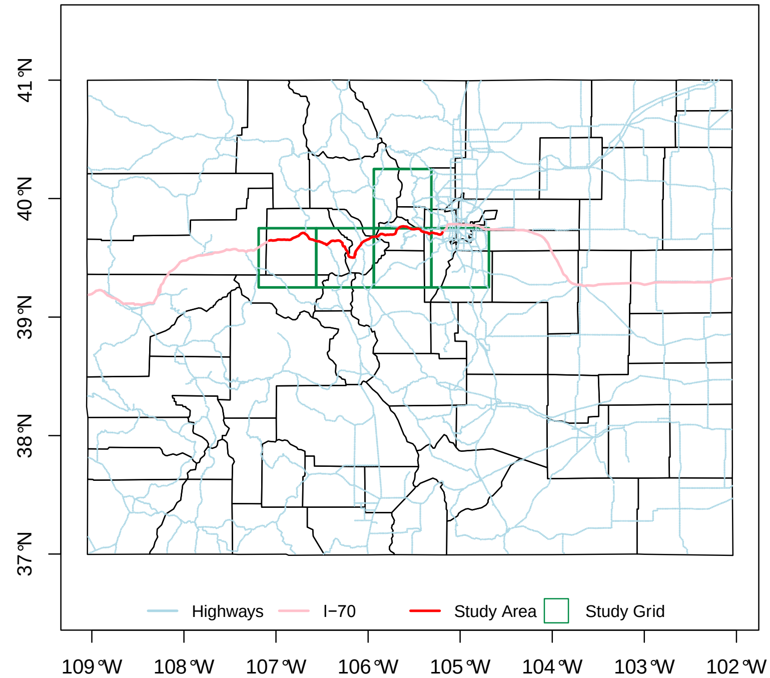

Figure 5. Colorado road network, AR grid cells, and study region

The data included all CDOT incidents that occurred in the study region during the period of March 1 to March 31, 2019, a month known for the occurrence of extreme avalanches in Colorado. Over the 31 days, there were 10 days classified as AR days. The impacts of AR conditions are presented in Table 4.

Table 4. Impacts of ARs on I-70 incidents and road closures

Variable	Mean No AR	Mean AR	Difference	% difference	p-value
Full closure (Hours)	2.36	20.5	18.14	768.6	0.0053 **
Chain restrictions	0.682	4.9	4.218	618.5	<0.001 ***
Hour-miles	296	2090	1794	606.1	<0.001 ***
Spinout	0.409	2.7	2.291	560.1	0.0016 **
Duration (hours)	28.1	121	92.9	330.6	<0.001 ***
Severity: moderate	1.36	4.3	2.94	216.2	<0.001 ***
Full closures	1.59	4.8	3.21	201.9	0.012 *
Events	11	19.3	8.3	75.5	0.0048 **
Severity: severe	8.5	13.7	5.2	61.2	0.055
Incidents	10.2	14.2	4	39.2	0.186
Partial closure (Hours)	7.64	9.95	2.31	30.2	0.654
Severity: minimal	1.09	1.3	0.21	19.3	0.827
Debris	1.14	1.3	0.16	14	0.984
Partial closures	4	4.3	0.3	7.5	0.892
Crashes	2.95	2.8	-0.15	-5.1	0.522
Traffic	0.864	0.5	-0.364	-42.1	0.303

Data from I-70 mile marker 156 to 240 from March 1 to March 31, 2019 with 10 days with AR conditions. Significance: *** p <0.001; ** p <0.01; * p <0.05 on linear regressions (equivalent here to analysis of covariance) controlling for day of week effects. Variables are ordered by percent difference in descending order. AR conditions: at least one six-hour period with AR conditions in the spatial grid cells, which cover the road extent on the day in question, using the Guan and Waliser (2015) MERRA-2 AR detection algorithm.

While ARs are known to cause avalanches (e.g., Hatchett et al. 2020), this analysis does not explicitly consider the impact of avalanches due to ARs on road events, as information on specific avalanche occurrences on I-70 were not present in the data. A specific exploration of the links between ARs, avalanches, and road impacts is a potential area for future research.

Of all the variables, the mean duration of full road closures (eastbound, westbound, or both directions) was most affected by AR conditions, increasing from a mean of 2.4 hours on non-AR days to 20.5 hours on AR days, over the 168 mile domain (84 miles in each direction). This is more than an eightfold increase in closure durations. At least some portion of I-70 was effectively closed on AR days during this study period. The increase in the number of hour-miles of closures from 296 to 2,090 can be translated into more meaningful metrics by dividing by the 168 miles in the domain. On an average non-AR day, there was a road closure in effect somewhere on I-70 in the study domain for 1 hour and 46 minutes. On an average AR day, this rose to 12 hours and 26 minutes, a sevenfold increase. The number of full closures per day increased from 1.6 to 4.8. The number and duration of partial closures also increased on AR days, although the increases were not as large or significant as the increases in full closures.

The duration of all incidents from the time they were reported to the time they were resolved increased from 28 to 121 hours. The number of events increased from 11 to 19 per day. A full description of the types and frequencies of events are provided in Table 5.

Table 5. CDOT number of events by sub types

Event sub type	# of events	% of events
Crash	93	21.4
Safety closure	48	11.1
Mechanical	45	10.4
Chain Law Code 18	38	8.8
Debris	38	8.8
Spun out/Slide off	36	8.3
Snow removal ops	29	6.7
Chain Law Code 15	26	6.0
Heavy traffic	24	5.5
Emergency roadwork	15	3.5
Outside agency activity	15	3.5
Environmental	9	2.1
Runaway ramp closure	8	1.8
Continuous flow metering	5	1.2
Warning	3	0.7
Abandoned vehicle	1	0.2
Road open	1	0.2

Events of all severity levels increased, although differences were only significant at the 5% level for moderate events. The lack of statistical significance for other events is likely due to the low power of the tests, given the small sample size of 31 days. Unsurprisingly, chain restrictions were more likely to be in effect during AR events.

Finally, and interestingly, the number of crashes and traffic incidents decreased on AR days. Although the differences are not statistically significant, the observed differences in means are likely due to the road closures: when roads are closed there are fewer crashes and fewer traffic incidents. In most studies, adverse weather is associated with increases in crashes (indeed, this is observed at the Utah sites as described in the next chapter), but adverse weather is also associated with decreased traffic flow rates through reduced demand, as some drivers cancel or postpone trips. The relationship between crashes and flow rates is complex, but under normal conditions the number of crashes varies directly with traffic flow. Generally, the worsening of road conditions due to adverse weather has a greater impact on the number of crashes than the associated reductions in traffic flow rates, but in extreme cases, such as that observed here, the effects can be reversed. However, even here the size of the effect is very small (5%) and not statistically significant.

In this case study, the effects on road closures were the most pronounced. To estimate the direct costs in terms of delays associated with the closures, data on traffic volumes were obtained from the CDOT OTIS for the month of March 2019. Mean non-AR and AR traffic flows over the study domain, averaged over six monitoring stations in both directions, are presented by time of day in Figure 6. The timing of road closures was fairly uniformly distributed by time of day or night, but the greatest impacts occurred during normal driving hours.

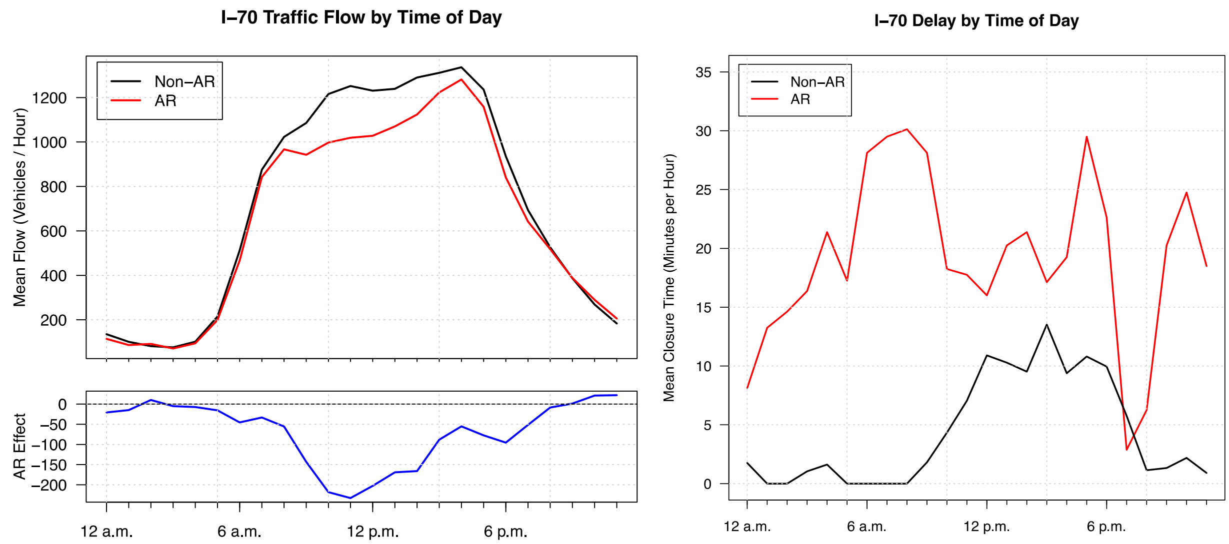

Figure 6. Impact of ARs on I-70 traffic flow by time of day

Hourly traffic flow rates were linked to the number of minutes of full closures per hour in each direction. Through a series of regressions of traffic flow on closure states, stratified by direction (east, west) and controlling for time of day, AR days were found to increase delays by 5,218 vehicle hours over the study domain. Assuming average occupancy of passenger cars of 1.5 persons and using delay costs of $17.81 per person per hour in passenger cars and $53.69 for commercial trucks (Ellis 2017), the average cost of delay time is $28.76 per hour in 2021 dollars. OTIS AADT flow rates by vehicle type were used in this calculation: 92.4% of vehicles over the study domain were assumed to be passenger vehicles, and 7.6% of vehicles were assumed to be commercial trucks.

With these estimates, the cost of AR-related delays due to road closures was estimated to be $160,000 per day, or $1.6 million for the month of March 2019.

These cost estimates included only time costs and did not include fuel or maintenance costs. Further, the estimates did not compare flow rates in March 2019 to average March flow rates, which would allow for the estimation of the number and cost of trips canceled or postponed. I-70 is not only the primary east-west freeway in Colorado, but the 84 mile section considered in this study is the main route from Denver to over a dozen economically important ski resorts, including Aspen and Vail. The economic impacts of AR-related road closures on this section of I-70 to ski resorts and to winter mountain tourism more broadly are likely to be significantly larger than the road travel delay times estimated here. On the other hand, ARs and AR-related snowfall are likely to increase demand at the ski resorts, which may offset the negative effects of road closures. It may be possible to separate these effects with additional data on lift ticket purchases or vacation rental rates.

CASE STUDIES: UTAH

Utah road networks are shown in Figure 7 with the AR grid cells for the study sites. In each figure, the freeway of interest is indicated in pink, with the section of interest indicated in red. The AR grid cells that intersect the study region are outlined in green.

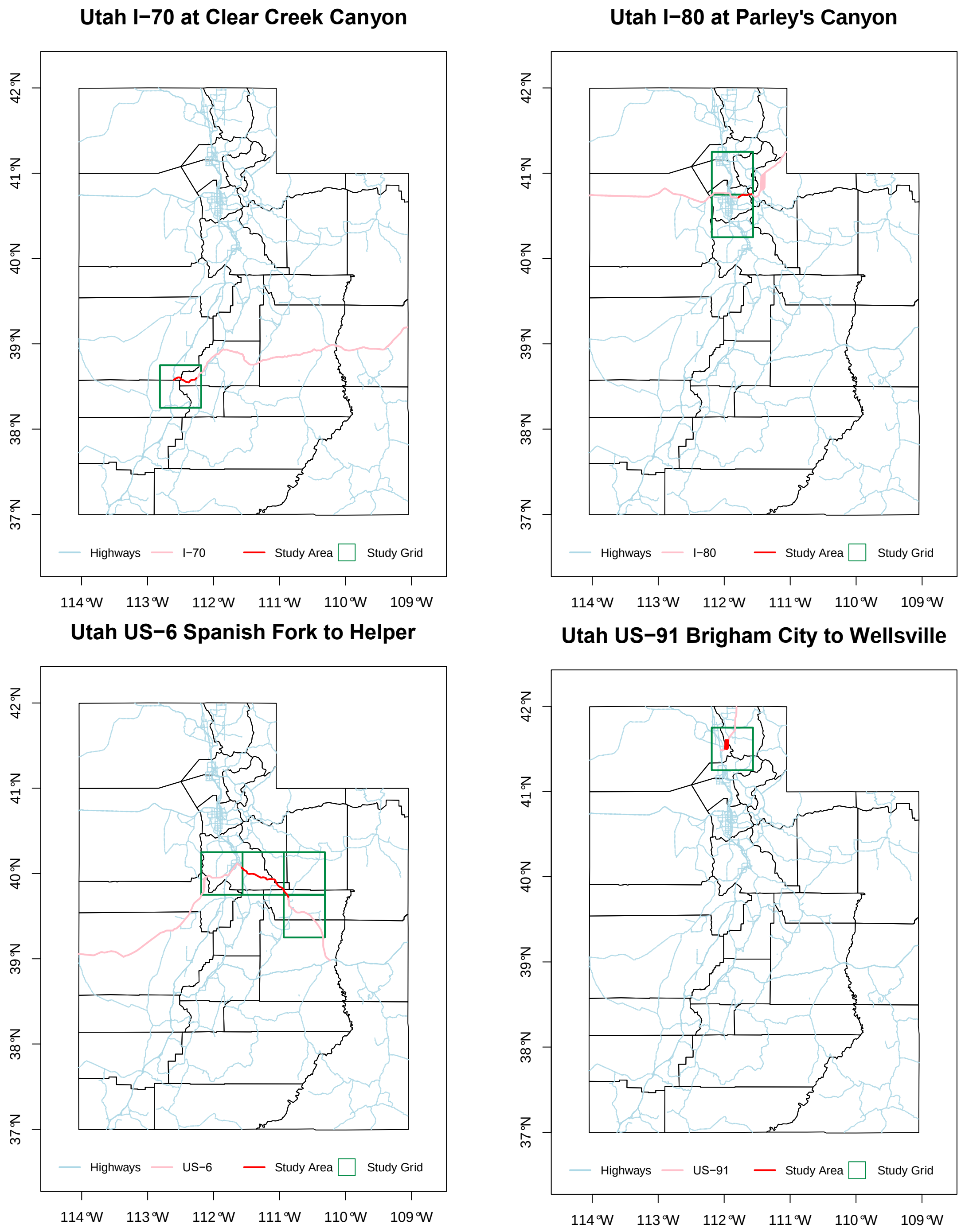

Figure 7. Utah road network, AR grid cells, and study regions

ARs were associated with increases in all key mobility and road safety metrics for the Utah study areas. Annual increases in crash costs associated with ARs ranged from $42,000 to $376,000 (Table 6). The total average annual cost of AR-related increases in crashes over baseline for the four sites was $710,000.

Table 6. Costs of crashes due to AR conditions at Utah sites

Site	I-70	I-80	US 6	US 91
Miles of freeway	24	13	52	13
Days in sample	2,571	2,639	2,635	2,156
Number of non-AR days	2,164	2,162	2,089	1,767
Number of AR days	407	477	546	389
Annual number of crashes	22	222	112	26
Annual number of crashes on non-AR days	118	1260	539	104
Annual number of crashes on AR days	36	344	267	49
Annual AR crashes above non-AR baseline	2.0	9.1	17.5	4.4
Annual crash cost ($)	471,000	4,778,000	2,404,000	558,000
Annual crash cost on non-AR days ($)	360,000	3,754,000	1,607,000	379,000
Annual crash cost on AR days ($)	110,000	1,024,000	796,000	179,000
Annual AR crash cost above baseline ($)	42,000	196,000	376,000	95,000
Annual cost per mile ($)	20,000	368,000	46,000	43,000
Annual cost per mile on non-AR days ($)	15,000	289,000	31,000	29,000
Annual cost per mile on AR days ($)	5,000	79,000	15,000	14,000
Annual AR cost per mile above baseline ($)	2,000	15,000	7,000	7,000

I-70 at Clear Creek Canyon

This section of the Utah study area included AR data from December 17, 2012 to December 31, 2019, a total of 2,571 days that included 407 AR days. The study area was along I-70 from milepost 0 to 23 (24 miles).

All incident metrics increased on AR days (Table 7).

Table 7. Impacts of ARs on I-70 at Clear Creek Canyon

Variable	Mean No AR	Mean AR	Difference	% difference	p-value
Events	0.0652	0.1007	0.0355	54.4	0.09
Crashes	0.0545	0.0885	0.0340	62.4	0.08
Partial closures	0.0065	0.0098	0.0033	50.8	0.51
Full closures	0.0009	0.0025	0.0016	177.8	0.43
Duration (hours)	6.65	9.45	2.79	41.9	0.28
Impact (1-10)	0.0850	0.1744	0.0894	105.2	0.01

Increases in events and crashes were 54% and 62%, respectively, with p-values <0.1 on the two-way hypothesis test of a non-zero AR impact in a linear regression or analysis of covariance framework, controlling for day of week and holiday effects. Partial and full closures increased by 51% and 178%, respectively, although the effects were not statistically significant. Duration of events increased by 42%, but the increase was not statistically significant. Finally, the mean sum of impact metrics over all events on a given day doubled.

Crash cost statistics from Blincoe et al. (2015) yielded a per-crash cost estimate of $21,500 in 2021 dollars. Using this estimate, the average annual cost of crashes over the I-70 Clear Creek Canyon domain was $471,000, including AR and non-AR days (shown previously in Table 6).

The crash costs attributable to AR events (i.e., the difference between actual annual cost and estimated annual cost assuming no AR days, labeled in Table 6 as Annual AR Crash Cost Above non-AR Baseline) were $42,000, roughly the cost of two additional crashes per year over the domain. For comparison with other sites, the average annual crash cost per mile at Clear Creek Canyon was $20,000, of which $2,000 per mile was attributable to AR events.

I-80 at Parley's Canyon

This section of the Utah study area included AR data from October 10, 2012 to December 31, 2019, a total of 2,639 days that included 477 AR days. The study area was along I-80 from milepost 129 to 141 (13 miles).

All incident metrics increased on AR days. Crashes increased by 23.7% on AR days (Table 8).

Table 8. Impacts of ARs on I-80 at Parley's Canyon

Variable	Mean No AR	Mean AR	Difference	% difference	p-value
Events	0.7655	0.9811	0.216	28.2	8.5×10^{-4}
Crashes	0.5828	0.7212	0.138	23.7	0.013
Partial closures	0.1619	0.2180	0.0561	34.7	0.019
Full closures	0.0088	0.0147	0.0059	67.0	0.27
Duration (hours)	71.75	105.99	34.20	47.7	0.056
Impact (1-10)	1.3571	1.8805	0.523	38.6	0.0053

On average, there were 222 crashes per year at this site, costing $4.8 million, of which 9.1 crashes were attributable to AR conditions, generating a cost of $196,000 over what would have been expected with no AR days. The average annual crash cost per mile at Parley's Canyon was $368,000, significantly higher than annual costs per mile at other sites. Of this, annual costs of $15,000 per mile were attributable to AR events, more than double the per mile costs at the US 6 and US 91 sites, and more than seven times the per mile costs at the I-70 Clear Creek Canyon site.

US 6 from Spanish Fork to Helper

This section of the Utah study area included AR data from October 14, 2012 to December 31, 2019, a total of 2,635 days that included 546 AR days. The study area was along US 6 from milepost 179 to 230 (52 miles).

All incident metrics increased on AR days. Crashes increased by 89.5% on AR days (Table 9).

Table 9. Impacts of ARs on US 6 from Spanish Fork to Helper

Variable	Mean No AR	Mean AR	Difference	% difference	p-value
Events	0.3040	0.5696	0.2660	87.4	4.6×10^{-12}
Crashes	0.2580	0.4890	0.2310	89.5	2.63×10^{-11}
Partial closures	0.0359	0.0714	0.0355	98.9	9.22×10^{-4}
Full closures	0.0105	0.0330	0.0225	214.3	7.55×10^{-4}
Duration (hours)	30.69	73.05	42.40	138.0	3.81×10^{-9}
Impact (1-10)	0.6395	1.3022	0.6630	103.6	3.81×10^{-8}

At this site, average annual crash costs of $376,000 were attributable to ARs. These were the highest average annual AR-related crash costs over the four sites, largely due to the 52 mile length of the test site. On a per-mile basis, the average annual AR-related crash costs were $7,000 per mile.

US 91 from Brigham City to Wellsville

This section of the Utah study area included AR data from February 5, 2012 to December 31, 2019, a total of 2,156 days that included 389 AR days. The study area was along US 91 from milepost 4 to 16 (13 miles).

All incident metrics increased on AR days. Crashes increased by 113.9% on AR days (Table 10).

Table 10. Impacts of ARs on US 91 from Brigham City to Wellsville

Variable	Mean No AR	Mean AR	Difference	% difference	p-value
Events	0.0668	0.1337	0.0669	100.1	0.0022
Crashes	0.0589	0.1260	0.0671	113.9	6.12×10^{-4}
Partial closures	0.0079	0.0180	0.0101	127.8	0.083
Full closures	0.0023	0.0051	0.0028	121.7	0.28
Duration (hours)	4.62	7.60	2.98	64.5	0.06
Impact (1-10)	0.1347	0.2211	0.0864	64.1	0.10

At this site, average annual crash costs of $95,000 were attributable to ARs. On a per-mile basis, the average annual AR-related crash costs were $7,000 per mile.

CONCLUSIONS

Main Results

California

In California, ARs were found to decrease average daily traffic flow rates on I-5 by 3.8% to 5.5% in northern California and the Bay Area, depending on event severity, and by 2.5% to 6.4% in southern and central California. Using the Ralph et al. (2019) AR ranking system, extreme AR4 and exceptional AR5 events reduced traffic flow by 7% to 18%, with greater percent reductions in northern California and the Bay Area and greater absolute reductions in numbers of vehicles per day in southern California.

The direct costs associated with reductions in passenger car VMT due to ARs were estimated at $106 million per year. Here, cost is quantified as the change in consumer surplus associated with the reduction in VMT due to AR conditions. The final cost estimate was dependent on a number of simplifying assumptions, including a linear demand relationship for each region of I-5 and a demand elasticity of -0.22 at the equilibrium VMT price and quantity. Over a plausible range of alternative VMT demand elasticities, the possible range of AR costs on I-5 was $67 million to $467 million per year. Improved estimates of annual AR mobility costs could be obtained by using higher frequency data and more sophisticated modeling techniques.

Colorado

In Colorado, AR impacts on a number of mobility and road safety outcomes were quantified on an important 84 mile stretch of I-70 west of Denver during March 2019. In spite of a small sample size, ARs were found to have significant impacts on the duration of road closures, the number of spinouts, moderately severe events, and the imposition of chain restrictions. Crashes and traffic incidents decreased in frequency, likely due to the increased durations of road closures and attendant decreases in traffic flow. The costs of AR-associated increases in delay times due to road closures were estimated at $1.6 million over the 10 AR days in the 31 day sample.

Utah

The Utah case study quantified the impacts of ARs on crashes, road closures, and delays from 2012 to 2019 at four sites: I-80 at Parley’s Canyon, I-70 at Clear Creek Canyon, US 6 from Spanish Fork to Helper, and US 91 from Brigham City to Wellsville.

Across all four sites, ARs were consistently associated with increases in the number of crashes, the daily cumulative event impact classification, and the number and duration of partial and full road closures. Percent increases in events and crashes were greatest at the US 91 site. Percent increases in number and duration of road closures were greatest at the US 6 site.

Increases in crash costs associated with ARs were calculated at the four sites. The average annual increase in crash costs due to ARs was estimated at $710,000, with the greatest annual cost impact of $376,000 observed over the 52 mile stretch of US 6, and the greatest cost per mile impact of $15,000 observed over the 13 mile stretch of I-80 at Parley's Canyon. It should be noted that these cost impacts do not indicate the total cost of crashes on AR days but instead the increase in cost on an AR day relative to a baseline non-AR day.

Limitations and Extensions

Different analyses were conducted in each state owing in part to differences in data availability. With additional data at each site, comparable cost estimates of the impacts of ARs on mobility, road closures, delay times, and road safety could be generated. Costs and impacts could then be compared across sites, in absolute terms, on a per-mile basis, or on per-VMT or per-vehicle hours traveled (VHT) bases. Such information would be useful in prioritizing resource allocations within road management agencies and investments in road weather safety systems.

This study focused on estimating the direct impacts and costs of ARs to road users in terms of mobility and road safety. A significant cost of adverse weather that was not considered is the cost to road management agencies of road maintenance and weather response. With data on road maintenance and road safety response efforts, the direct costs of ARs to road management agencies could be estimated and compared to the costs of ARs to road users.

California

Daily census data are used in the California analysis of AR impacts on traffic flows for ease of analysis. Caltrans daily V-class census data are limited to the period of 1996 to 2016. Improved estimates could be obtained by using more recent higher-frequency data from a wider sensor network.

The California VMT cost estimates derived from data over the period of 2010 to 2019 were highly sensitive to the functional form of the demand function, which was chosen to be linear to simplify the analysis. Other methods could be used to estimate the direct elasticity of VMT to total costs of VMT, including weather-related costs, rather than relying on the elasticity of VMT with respect to gasoline costs that make up only a fraction of total costs of VMT. Finally, more sophisticated methods could be used to estimate the change in consumer surplus associated with reductions in VMT.

Colorado

The Colorado study was limited to a single month due to the initial data request, which was chosen to focus on a location and time period where extreme adverse weather events were known to have caused a number of road closures. Extending the direct impact analysis to a longer time series and a wider spatial domain could provide additional useful information on the impacts of lower intensity events.

The estimates of AR impacts on delay costs associated with road closures relied on statistical methods that quantified mean AR effects and then applied these values to observed hourly traffic volumes to estimate delay times. Improved delay times results could be obtained more directly from the available data by explicitly making use of the locations of closures. Such an approach would generate more accurate measurements of user costs.

Finally, the VHT delay times and associated cost estimates did not explicitly consider the costs of detours or changes of destination. Many I-70 road users are sophisticated consumers of weather forecast information and are often well aware of road conditions before planning or making a trip. Hence, the costs of trips avoided or canceled may significantly exceed delay costs associated with road closures. These costs were not quantified in this analysis.

Utah

The Utah sites covered areas of key concern to road managers but of relatively limited spatial domains. Extending the domain could yield useful information on impacts to the broader state transportation network. Due to data limitations on the precise location and timing of road closures, and the chosen focus on incident rather than mobility data, only the direct costs of crashes were estimated in the economic analysis. The other case studies indicated that the impacts of ARs on mobility may be more costly than the road safety impacts at these sites. Finally, average crash costs were used in the cost estimation procedure. More precise estimates could be generated by taking crash severity into account. If data on type and number of vehicles per crash were available, these could further improve the accuracy of cost estimates.

Cost Estimation

Cost estimates in each of the case studies were sensitive to value of time and vehicle operating cost parameters. Allowances were made for the fraction of observed traffic accounted for by passenger vehicles and commercial trucks, but further improvements in cost estimates could be obtained by allowing cost components to vary by location and over time.

AR Classification

The Guan and Waliser (2019) AR detection algorithm uses a location-specific IVT threshold of the 85th percentile at each location. This has the advantage that it allows for the quantification of impacts in areas with diverse topographic and meteorological characteristics. It may, however, also be useful to consider ARs based on fixed IVT thresholds, e.g., those with IVT over 250 kg m^{-1} s^{-1} over some fixed duration. This would more accurately account for the variation in frequency of ARs over the western US.

Future Research

Use and Value of AR Forecasts in Road Management

AR observation networks and forecasting capabilities have improved significantly in recent years (Ralph et al. 2020). Skillful forecasts of AR landfall location, duration, and intensity are available with lead times of up to one week from dynamical models (Martin et al. 2018) and machine learning methods built on them in a postprocessing framework (Chapman et al. 2019). Preliminary results for longer-lead forecasts up to two weeks ahead are encouraging, as are subseasonal (from two to four weeks per DeFlorio et al. 2019) and seasonal (two to six months per Gibson et al. 2021) forecasts. The short-term forecasts present clear operational opportunities, and the longer-term forecasts offer improvements over climatology and could potentially have value for operations.

Weather forecasts have long been used to predict adverse road weather events and to inform operational road management decision-making (Lawrence et al. 2014). Road weather management information systems (RWMISs) are a fundamental component of the road management toolkit. Improved AR forecast technologies could be used to improve existing RWMIS capabilities. Dynamic traffic signals (DTS) and maintenance decision-support systems (MDSS) in particular could benefit from AR forecasts.

Finally, climate change is predicted to change the frequency, magnitude and spatial distribution of ARs (Dettinger 2011). As AR projections improve, they could be used to inform long-term (i.e., decadal) planning and road infrastructure investment decisions.

Development of an Operational AR Transportation Impact Index

Of potential value to road management agencies would be the development of an operational AR transportation impacts index. Such an index, similar in form to the Ralph et al. (2019) AR ranking scale, could be used by road managers to inform the public of risks on roadways and to allocate road weather maintenance and response resources ahead of significant AR events. Economic methods (e.g., Murphy and Katz 2005) could then be used to quantify the value of such a tool and of AR forecast technologies more generally.

Impacts of ARs on Freight Transportation Networks

A number of studies have quantified the impacts of adverse weather on trucking and freight networks (Mesa-Arango et al. 2013, 2016; Krechmer et al. 2012, 2016). A similar analysis could be conducted to quantify the impacts of ARs on trucking and freight in the western US, both in terms of closures of major freeways, particularly over mountain passes, and of AR-related inclement weather in high density areas or areas with existing freight network bottlenecks. Recently developed INRIX probe data could be used in such an analysis, in addition to the network models described in previous studies in the literature.

Broader Economic Impacts of AR-Related Road Disruptions

The present study considered only the direct economic impacts of ARs on road closures, crashes, and reductions in traffic flows. In the intermountain west, ski resorts provide significant winter revenue to mountain communities. With sales and revenue data from ski resorts or with data from vacation rental providers, it may be possible to quantify the broader economic impacts of AR-related road closures and adverse road weather conditions on the winter mountain tourism sector in these regions.

Furthermore, traffic congestion and increased delay times associated with ARs in more densely populated areas may have spillover effects on local and regional economies. Disruptions in freight networks have been shown to have significant economic costs (Mesa-Arango et al. 2013, 2016), but there may be additional impacts in terms of retail sales and revenues. High resolution retail sales data, combined with state DOT and AR data, could potentially be used to quantify these impacts.

National Analysis of AR Transportation Impacts

ARs predominantly affect the west coasts of the world's major landmasses. The analyses developed in this study could be readily extended to consider impacts in Washington and Oregon. West Coast ARs can penetrate inland through the Transverse and Peninsular Ranges of southern California and Baja California, Mexico to impact Arizona, Utah, and Colorado, generating the types of impacts quantified in this study. Similarly, ARs have been shown to penetrate inland through the Columbia River Gorge in Washington, generating impacts as far east as Idaho and Montana. Additionally, recent research indicates that some ARs or AR-like structures pass over the Gulf of Mexico and impact the eastern US (Mahoney et al. 2016, Martinez-Claros et al. 2020). Hence, the methods developed in this study could also be applied beyond the western US.

Road safety and mobility data could be obtained from state DOTs in the coastal states of Washington and Oregon and inland states of Arizona and Idaho to extend AR impact analyses to these regions. In California, the combination of Caltrans PeMS data and AR occurrence and intensity data could be used to quantify impacts on other major freeways, or potentially for the entire state's network of freeways and arterial roads. A complete national analysis of AR impacts would require the collection and processing of data from all state DOTs on mobility, road safety, staffing and maintenance, and freight network flows. Such an analysis would provide road managers and policymakers a complete picture of AR impacts on road networks across the US, allowing for improved response strategies and allocations of resources to mitigate the adverse impacts and outcomes.

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