Wyoming's
Ground Emergency Medical Services

a primer on

operations, costs

and potential

revenue

Wyoming Department of Health

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Very few communities provide sufficient financial support for adequate ambulance services. Where they are provided, they are usually maintained by the fire or police department. Many volunteer, nonprofit rescue squads and local ambulance groups provide commendable service and in many small communities this system would seem to meet basic, but usually only minimal needs. Approximately 50 percent of the country's ambulance services are provided by 12,000 morticians, mainly because their vehicles can accommodate transportation on litters.

—"Accidental death and disability." Nat'l Academy of Sciences. (1966)

Acknowledgements

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Contents

1 Executive summary

This report describes the landscape of Wyoming's ground Emergency Medical Services (EMS) providers, with the goal of framing recommendations to improve the EMS system's long-term financial sustainability.

1.1 Findings

Some of the main observations from this report include:

1.1.1 Volume and risk vary over demographics and across geography

- 44 EMS providers in Wyoming respond to ~ 77.5K calls per year.
- Of these calls, around 37.3K are 911 responses and 12.3K are inter-facility[1] transports. These are reimbursable calls, meaning EMS services can be paid for them by most public and private health insurers.
- The remaining ~ 34% of calls are *not* reimbursable. Most of these are "lift assists," where ambulance personnel help someone who has fallen but cannot get up.
- The vast majority of EMS calls happen locally. Highway crashes only account for 1-2% of EMS responses.
- The risk of finding yourself in need of an ambulance increases exponentially with age. Medicare is thus one of the largest payers for EMS, with 40-50% of total call volume.

1.1.2 Revenue from service volume is usually too low to cover the fixed costs of readiness

- The costs of EMS are fixed, because they are based around a need for readiness. Statewide, we estimate that between 71 (off-peak) to 113 (peak) ambulances are required to be on call at any given moment, at a cost of **~ $66.5 million** dollars per year.
- Unlike costs, EMS revenue is variable. Where the largest services can expect to get paid for 9,000 - 10,000 calls per year, many smaller services see fewer than 100 calls annually.
- If all reimbursable calls were actually billed, we anticipate the EMS system could collect **~ $36.7 million** dollars annually.
- The gap between fixed costs and variable revenue means that **~ $30 million** is required to subsidize EMS operations in Wyoming each year. Subsidies include a mix of tax dollars, volunteer labor, hospital-based revenue, fundraising, and grants.
- Some subsidy sources are more sustainable than others. Volunteer labor, once the bedrock of rural EMS, is no longer reliable.

[1] E.g. hospital to hospital.

1.1.3 Larger, full-time services generally have faster response times

- Expected response times for EMS services vary, largely by agency size. The most critical variable is "chute time," or the time between dispatch notifying the ambulance and the time it starts rolling. Because they have paid staff ready to go, the larger, full-time agencies can be on the move in under a minute. Smaller, volunteer-based agencies often have chute times between 5-10 minutes.
- Around 58% of Wyoming's population lives in an area with an expected response time under 9 minutes, 36% live within a response time area of 9 to 30 minutes, and the remaining 6% live in an area outside 30 minutes.
- This percentage varies significantly across the State. Weston, Crook, Niobrara, and Fremont counties have the largest percentage of people (> 10%) living over 30 minutes from an ambulance. The Wind River Reservation, in particular, has one of the highest absolute numbers of people living in this zone.

1.2 Recommendations

In light of these findings, we recommend pursuing an incremental approach, designed to increase efficiency while improving long-term sustainability:

- First, the State should **explore the competitive procurement of a statewide billing contractor** to maximize service revenue. This contractor would use existing data from the Wyoming Ambulance Trip Reporting System (WATRS) to generate health insurance claims and submit them to payers. Participation in this system would be voluntary for EMS agencies. The contract could initially be pursued in the absence of any statutory changes or appropriation from the Legislature. If successful, this could cut administrative costs, improve billing and collection rates, reduce the barriers to entry for smaller EMS agencies, and improve data quality.
- Second, the Legislature should **appropriate targeted State matching funds** designed to encourage local decisionmakers to push their EMS systems towards more sustainable revenue streams, like fire/EMS models and Critical Access Hospital cost-based reimbursement.

Neither solution is a silver bullet to filling the ~ $30 million gap between annual costs and revenue, but both are cost-effective and tailored ways to help the EMS system help itself for the long-term.

2 About this report

The primary objective of this report is to provide State and local decisionmakers background on the landscape of EMS in Wyoming. While these facts and figures are intended to frame recommendations for system sustainability, they are hopefully useful in their own right.

2.1 What do we mean by ground EMS?

We mean ground ambulance services. These are organizations of trained medical professionals (Emergency Medical Technicians, paramedics, and various levels in between) who respond to emergencies using a specialized truck (the ambulance), and then provide life support services to patients while transporting them to higher levels of care.

We are excluding air ambulance providers from this analysis. Air ambulances provide similar medical treatment as ground EMS, but use airplanes and helicopters to transport patients.

2.2 Primary research questions and caveats

Some of the questions we try to answer here include:

- Where does EMS volume occur?
- What ambulance service is likely to respond to calls in each corner of the State, and how long will it take them to do so?
- How many ambulances are necessary to be able to respond to calls?
- How much should those ambulances cost?
- What kind of revenue do EMS agencies receive, and how well does that cover costs?

We do not have exact answers to these questions. Standardized data on costs and revenues for all EMS agencies, for example, doesn't exist. We therefore use estimates and statistical models[2] to fill in these gaps, with the goal of getting in the ballpark.

With this caveat, we also note that interviews with EMS agencies[3] around the State have largely confirmed that these estimates are "close enough" for the purpose of illustrating our major findings and giving decisionmakers some material to chew on.

2.3 How to navigate this report

This report is intended as a reference, not necessarily cover-to-cover bedtime reading. We have a lot of maps and charts that are agency- or county-specific, and if this is all you're looking for, the Table of Contents is your friend.

You may have already noticed that the Table of Contents outlines this report, similarly to the Executive Summary, and will communicate ~ 90% of the gist. What you might not know is that —at least if you're reading this as an electronic *.pdf document —each line of the Table of Contents links directly to the relevant section, in order to make it easy to skip to what you care about. Additionally, if you click on

[2] As the statistician George Box noted: "All models are wrong. Some are useful."

[3] See the acknowledgements before the table of contents.

the footers at the bottom of each page ("Wyoming Department of Health"), you'll get right back to the Table.

We hope that these features make this report easier to navigate.

At the very end is the Technical Appendix. This is included to "show our work," not provide any additional substantive insights or be a particularly enjoyable read.

3 What is the problem we're trying to solve?

The main problem is money. The health policy euphemism for this is "sustainability."

3.1 The gap between revenue and costs

More precisely, in most of the State, or at least outside the bigger cities, we see a significant gap between reasonable costs (we estimate ~$67 million for the entire system) and potential service revenue (~$37 million). For agencies to survive, this ~ $30 million gap has to be filled by various subsidies, some of which are more sustainable than others.

Why is this the case? Why can't revenue cover costs? The simple answer is that service volume is usually too low to cover the cost of readiness, particularly in rural and frontier areas.

3.1.1 Costs are based on readiness and are largely fixed

The purpose of EMS is to rapidly respond to people with medical emergencies, stabilize their medical situation to the greatest extent possible, and quickly get the person to the most appropriate level of care. Speed and medical expertise are both critical aspects of the service.

This means that even the smallest agencies in Wyoming must always —24 hours of the day, 7 days a week, 365 days a year —have *at least* one ambulance ready to go on short notice. Larger agencies usually need two to four in order to deal with more than one call happening at the same time. Those ambulances have to be maintained, fueled, provisioned, and, most importantly, *staffed* with highly-qualified and dedicated people.

That readiness comes at a cost, and that cost is mostly fixed.

- Employees on call, for example, have to be paid regardless if they are responding or not. Labor costs makes up ~ 63% of the average total expenses of a rural ambulance service.[4]
- Most ancillary costs are also fixed. People need training to maintain proficiency. Ambulances need maintenance, equipment, facilities, and administrative support, regardless of call volume. And all capital assets depreciate over time.
- Requirements for higher standards of medical care increase these costs. Advanced Life Support (ALS) transports, for example, require staff with much more training (and commanding higher wages), as well as specialized equipment.

So what costs are truly variable —that is, depend on volume? Fuel, medical supplies, and other consumables. These represent a very small percentage of total cost structure for most services.

3.1.2 Revenue depends on volume

Ambulance services are not paid for this readiness. They make money from medical service calls, the volume of which generally depends on the number of people living in their service area. Each successful payment to the EMS agency depends on a specific chain of events happening:

[4] "Medicare Ground Ambulance Data Collection System (GADCS) Report - Year 1 and Year 2 Cohort Analysis." RAND Health Care. PR-A2743-7.

1. **Someone has a medical emergency**. The frequency at which this occurs is generally based on population served, though older people are at much higher risk than younger people (per the demographic risk section).
2. **That someone needs to be transported**. Generally, the service can't bill private and public health insurers if it doesn't physically take someone to the hospital. On average, only two-thirds of calls are transported. The remaining third (e.g., the paramedics help someone get to their feet in a "lift assist") are non-reimbursable.
3. **The ambulance service has to send a bill**. This is not simple. Health insurance claim forms are complex[5] and require significant documentation of diagnoses and the procedures performed. The ambulance service and its personnel not only need to be licensed and credentialed by the State, but also registered as providers with multiple public and private insurers. The patient has to provide accurate insurance information. All of this requires some degree of administrative overhead that some smaller services lack.
4. **Someone has to pay that bill**. If the person is covered by a public payer like Medicare or Medicaid, a "clean" (i.e., no billing mistakes) ambulance claim will usually pay quickly. But these public payers usually pay significantly lower rates than private insurers.

   Conversely, while private insurers usually pay better, getting paid can be a hassle, depending on how the insurer handles its provider relationships (e.g., claims denials, stretching out its payables, or limiting networks).

   If the patient is uninsured, owes a significant deductible or cost-sharing, or is "balance billed" because the insurer is out-of-network,[6] the headache intensifies for everyone. People don't pay. Services turn to billing specialists, or sell debt to collections agencies for pennies on the dollar. Credit scores are ruined. And people still don't pay —on average, the uninsured only end up paying an average of 25 to 35% of their medical costs.[7]

Getting paid for services is therefore not straightforward. And because service volume scales with population, the gap between fixed costs and variable revenue grows wider and wider for smaller services who cover more rural areas.

3.2 Various subsidies fill the gap

Outside of service revenue, EMS agencies cobble together four major categories of other funding we'll call "subsidies" in this report:

- **Tax dollars**, whether supporting EMS directly through county mills, a service district or combined fire/EMS agency;
- **Hospital-based revenue**, to include cross-trained Emergency Department/ambulance personnel and Critical Access Hospital (CAH) cost-based Medicare payments;

[5] https://www.nucc.org/images/stories/PDF/1500_claim_form_instruction_manual_2020_07-v8.pdf

[6] Unlike air ambulances, which are now largely prevented from balance billing people by the federal "No Surprises" Act (P.L. 116-260), ground EMS agencies are still allowed to do this.

[7] Finkelstein, et. al. "What does (formal) health insurance do, and for whom?" National Bureau of Economic Research. https://users.nber.org/~notom/research/Finkelstein_Mahoney_Notowidigdo_AR_Feb2018.pdf

- **Grants and fundraising**; and,
- **Volunteers**.

It's important to note that these subsidies are *already funding* the system that exists. Any kind of response time or quality improvements would require even more funding, since service volume won't change.

We do not (because we cannot) quantify how much each subsidy source contributes to the overall ~$30 million subsidy gap estimated by this report. Every EMS service has a different mix.

Why is this so?

3.2.1 Subsidies vary because EMS is a relatively new system, and has evolved haphazardly

While special-purpose ambulances and "ambulance attendants" were first employed during the Napoleonic wars,[8] EMS wasn't widespread in the civilian world until almost another 150 years. In fact, up until the 1950s, ambulance services provided little more than basic first aid.[9]

In 1966, the seminal EMS white paper, "Accidental Death and Disability: the Neglected Disease of Modern Society", was released by the National Academy of Sciences. The paper began with a description of how bad the problem had become, in contrast to the advances of battlefield medicine:

> Accidents are the leading cause of death among persons between the ages of 1 and 37; and they are the fourth leading cause of death at all ages. Among accidental deaths, those due to motor vehicles constitute the leading cause for all age groups under 75. Since 1903, when the "horseless carriage" toll assumed significance, there have been more than 6,500,000 deaths from accidents in this country, over 1,690,000 involving motor vehicles. In 1965, the accident death toll was approximately 107,000, including 49,000 from motor vehicles, 28,500 at home, and 14,100 at work. Deaths from traffic injuries have increased annually; 10,000 more were killed in 1965 than in 1955, and the increase from 1964 to 1965 was 3 percent. Seventy percent of the motor vehicle deaths occurred in rural areas and in communities with populations under 2500.
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> ...
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> Expert consultants returning from both Korea and Vietnam have publicly asserted that, if seriously wounded, their chances of survival would be better in the zone of combat than on the average city street. Excellence of initial first aid, efficiency of transportation, and energetic treatment of military casualties have proved to be major factors in the progressive decrease in death rates of battle casualties reaching medical facilities, from 8 percent in World War I, to 4.5 percent in World War II, to 2.5 percent in Korea, and to less than 2 percent in Vietnam.

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[8] In the United States, the first effective Ambulance Corps was developed by Maj. John Letterman, the medical director of the Army of the Potomac. Beginning in the summer of 1862, the Corps faced its first test at Antietam, refined its operations at Fredericksburg, and was fully operational by Gettysburg. By rapidly transporting the wounded to field hospitals, the Corps was able to halve the wounded death rate from 25.6% to 13.3%. Labbe. "A Complete Transformation of Medicine: John Letterman's Ambulance Corps." 2019. https://gettysburgcompiler.org/2019/01/09/a-complete-transformation-of-medicine-john-lettermans-ambulance-corps/

[9] This is the context for the epigraph at the beginning of this report.

Following the white paper, significant federal investment in EMS in the 1970s, including the adoption of the 911 system, led to increased standardization, to include the rigorous training and licensure requirements for EMTs and advanced practitioners that we see today.

Federal funding receded in the 1980s, however, leaving EMS systems to develop locally. As a result, each system has evolved in its own way since. Entities who deliver EMS today range from fire departments to municipal and county governments to private providers and hospital-based systems.

Wyoming is no exception to this diversity. While the profession itself remains standardized, this variation in administrative structure has created disparities in the funding that supports EMS around the State.

3.2.2 Some subsidies are more equal than others

These subsidies will always be necessary. Under current private and public payment rates, there is no scenario where revenue can pay for the cost of ambulance services in most of the State.

But some of these subsidies are more sustainable than others. The decline of volunteerism generally, for example, is well-documented.[10] In the world of EMS, the base of volunteers is aging and shrinking, requiring many small services to rely increasingly on paid personnel.[11]

We would therefore consider volunteer labor much less reliable than, say, enhanced Medicare payments for Critical Access Hospitals, though it is not unheard of for the federal government to change the rules of the game there either.

[10] Volunteer rates peaked in 2001, per https://dogood.umd.edu/sites/default/files/2019-07/Where%20Are%20Americas%20Volunteers_Research%20Brief%20_Nov%202018.pdf

[11] See: https://www.city-journal.org/article/an-overlooked-crisis, https://www.ruralhealthresearch.org/projects/576, and https://safetechsolutions.us/resource-library/the-real-cost-of-volunteerism-in-ems

4 What is the role of government?

Before moving on from this identified problem to any potential solutions, we'll spend a little time on this philosophical question and provide some background on the current role of the State.

4.1 Is EMS a public or a private good?

We mean this in the strict microeconomic sense, not implying any value judgment as to whether or not EMS should or shouldn't be provided publicly.

In this framing, "public goods" are defined by two primary characteristics:

- They are *non-rivalrous*, meaning that one person's consumption of the good doesn't affect or reduce other people's consumption; and,
- They are *non-excludable*, meaning that it isn't practical to prevent other people from consuming them for free.

Various examples of public goods include:

- Clean air;
- National defense;[12]
- Broadcast radio;
- Law enforcement;[13] and,
- Street lights and lighthouses.

This is the first question we need to answer: if EMS is a public good, there are strong arguments for government subsidies and regulation, since public goods are rarely provided by a free market. If, on the other hand, EMS is more of a private market good, the role of government should be more limited.

4.1.1 EMS doesn't fit neatly in either box

In the classic manner of bureaucrats,[14] we argue that EMS falls in-between these two classifications, and that the closest analog to EMS is that of a regulated utility, like the kind of company that provides water, gas, and electric service to your house.

On the one hand, EMS does not meet the criteria of a pure public good. EMS is *rivalrous*; while we pay for readiness, an ambulance responding to a call effectively prevents it from responding to someone else. EMS is also *excludable*. While services provide a lot of uncompensated care, they theoretically[15] could refuse to transport people to the hospital without payment.

[12] The operations of the US military to protect the people and interests of the United States apply to the country as a whole. The US can't exclude the State of Colorado from the nuclear deterrent, or the State of California from the benefits of freedom of navigation.

[13] Similar to defense, police investigating and preventing crime benefits society as a whole. There is no practical way to bill specific people for the effects of lower crime.

[14] An apocryphal story recalls President Truman angrily demanding a "one-armed economist" who could give him decisive policy recommendations.

[15] Assuming legal requirements to transport emergent and urgent cases, e.g., Chapter 4, Section 3(b) of Department of Health EMS rules, did not apply.

On the other hand, while EMS agencies do charge people (or their insurers) for services, the resemblance to a private market good ends quickly after that. Consider:

- EMS is an absolute requirement for anyone in a medical emergency. 911 is not a luxury good available only to those who can pay for it.
- As with most healthcare,[16] people do not and cannot make informed consumer decisions on emergency medical services. They are probably in significant distress or unconscious at the time of the 911 call, and even if they were lucid, they are likely unaware of the price they will be charged and the quality of the medical personnel who show up.
- Choice of providers is impractical because of the mismatch between costs and revenue. Albin Rescue, for example, covers a small corner of Laramie County with a volunteer ambulance. They responded to 18 calls last year. Imagine the inefficiency of operating a second ambulance —thereby doubling the costs and halving the revenue —in order to offer patients a choice of which ambulance should arrive.

4.1.2 The closest analogy to EMS is a public utility

This last point draws the connection to the utility model of a "regulated monopoly." Duplicative ambulance infrastructure would be just as inefficient as having competing water or natural gas companies lay their own service lines to your house.

If this premise is true, both the private market and government have important roles to play in the provision of EMS services. Where the private market is likely able to allocate labor and capital most efficiently at the micro level, the role of government is to:

- Decide which service should be the "monopoly" provider in each area, likely based on overall cost and quality criteria;
- Ensure public health and safety by credentialing providers and ensuring minimum standards are met; and,
- Subsidize the cost of EMS for the indigent.

This analogy isn't perfect. Governments also regulate utility rates (e.g. through the Public Service Commission) to protect consumers while giving companies an opportunity to earn a reasonable return on capital. This is generally not something that happens with EMS, though Medicare and Medicaid do pay set rates and have significant market share.

Given this theory, how does the *actual* role of government look? In the next sections, we start at the federal level and work down to the local.

4.2 Federal role as a payer

The federal regulatory role in EMS is small and generally limited to those facets "relating to the price, route, or service" of air ambulances, per the Airline Deregulation Act of 1978 and Federal Aviation Administration Authorization Act of 1994.[17]

[16] Only an estimated 30% of health services are truly "shoppable."

[17] Even then, the State exerts authority over the medical side of the air ambulance business.

The bigger role is that of an public insurer: Medicare, operated by the federal Centers for Medicare and Medicaid Services, is the single largest payer (40-50% of calls) for ground EMS transports. The rates that Medicare pays are not only critical to ambulance solvency (or lack thereof), but are also often the benchmark on which many private payer rates are set.

Other federal payers —the Veterans' Administration, TRICARE, and the Indian Health Services —play smaller roles, and cover distinct populations.

4.3 State role as both payer and regulator

The State is also a payer for the ~ 68,000 Wyoming Medicaid members and the ~ 40,000 State employees, retirees, and dependents covered by the Employees' and Officials' Group Insurance (EGI) plan. Between the two programs, the State's combined market share is probably between 15-25% of ambulance calls.

In addition to paying ground EMS claims, the State regulates ambulances and associated staff and conducts long-range planning through its Office of Emergency Medical Services (OEMS).

4.3.1 Regulatory authority of the Office of Emergency Medical Services (OEMS)

OEMS' authority to regulate ground EMS is found in W.S. 33-36-101 et. seq.. The Office specifically regulates two aspects of the profession:

- **Personnel**. Under W.S. 33-36-110, OEMS licenses ambulance personnel per their qualifications as an Emergency Medical Responder (EMR), Emergency Medical Technician (EMT), Advanced EMT, paramedic, and the like. Wyoming has adopted reciprocal licensing of personnel under the REPLICA interstate compact codified in W.S. 33-36-201 et. seq..
- **Businesses**. Under W.S. 33-36-104(a), OEMS "shall grant" ambulance business licences to any person who meets OEMS rule requirements.

4.3.2 Long-term policy, planning and technical assistance

The Department's long-term policy and planning role is codified in W.S. 35-1-801, which requires the Department to "develop a comprehensive emergency medical services and trauma system."

We execute this role through:

- Limited training, technical assistance, periodic local needs assessments, and other support funded by the Emergency Medical Services sustainability trust account (W.S. 33-36-115);
- Data collection through the Wyoming Ambulance Trip Reporting System (WATRS), which, in turn, informs both the regulatory actions we take and,
- Writing reports like this one.

4.4 County and local role as operators

Counties and local governments have varying relationships with the EMS services operating in their area, but, generally speaking, they do exercise direct or indirect control over operations and performance:

- Some fully own and operate the EMS service directly (e.g. Jackson and Laramie Fire/EMS);
- Others operate EMS through an intermediary (e.g. county-owned hospital or hospital district); and,
- Some contract with private entities to provide EMS coverage. Laramie County, for example, participates in a Joint Powers Board which gives exclusive EMS franchise to American Medical Response (AMR) in exchange for payment and requirements to meet performance standards.

4.5 How should the role of government change?

Given this background, we recommend thinking about the role of the State on the margin; i.e., instead of drastic changes or coming up with something *de novo*, the question is: should that role, as a payer or as a regulator, *increase* or *decrease*?

- **As a payer.** Increased involvement on the payer side, for example, would involve more funding through Medicaid, EGI, or direct grant awards;
- **As a regulator.** Should the State have more involvement in deciding efficient ambulance allocations, should it establish minimum quality standards, or should it reduce its role?

4.6 Previous ideas

EMS sustainability is not a new issue. Over the past decade, many ideas have been explored to put the system on more stable footing. Some have been implemented. This section provides some background on, and assesses the feasibility and/or results of, some of those proposals.

On each of the following subsections, we indicate whether a proposal remains an *idea* or if it has already been *implemented*.

4.6.1 Idea: Designate EMS as an essential service

This idea would put EMS on an "equal footing" with law enforcement, fire protection, and other "essential services" by codifying it in law as something that county or municipal governments must provide.[18]

While straightforward, this approach only improves sustainability to the extent it can deliver on the **unfunded liability** created for whichever entity is made responsible for providing EMS.

Most of these entities are already stretched thin. Of the twelve (12) allowed mills that counties can legally impose, for example, only Campbell and Teton counties are not at their maximum levy. Similarly, the list of cities and towns imposing fewer than the maximum 8 mills is also short.[19]

It's likely, therefore, that if EMS were made an essential service, some other county or municipal requirement would need to be cut for EMS to be funded, outside any a broader change to limits on mill levies.

[18] For example, counties shall have elected sheriffs who must maintain jails per W.S. 18-3-601 and 18-6-302(a), respectively. However, there are no such definitive statutes requiring fire protection or municipal police.

[19] Short enough that we can list them in this footnote: Albin, Alpine, Burlington, Burns, Chugwater, Cody, Cokeville, Diamondville, Dubois, Jackson, Kemmerer, Meeteetse, Opal, Pine Bluffs, Powell, Riverton, and Worland. Dept. of Revenue 2024 Annual Report, page 28-31.

4.6.2 Implemented: Establish Emergency Medical Service Districts

One option to loosen the constraint on taxing authority is the establishment of EMS Service Districts under W.S. 18-12-105 et. seq.. These districts were recently authorized by the Legislature[20] as a way for voters in a designated area to voluntarily tax themselves with up to four (4) additional mills to support EMS.

The last column of Table 1 shows the potential additional revenue an additional four mills might raise if imposed on a county-wide basis.[21]

Table 1: 2024 Mill Levy

County	County mills	County levied	EMS District (+4) potential
Albany	12.000	$8,169,420	$2,723,140
Big Horn	12.000	$3,321,457	$1,107,152
Campbell	10.950	$58,303,652	$21,298,138
Carbon	12.000	$9,408,315	$3,136,105
Converse	12.000	$42,723,785	$14,241,262
Crook	12.000	$3,819,010	$1,273,003
Fremont	12.000	$10,214,554	$3,404,851
Goshen	12.000	$3,668,947	$1,222,982
Hot Springs	12.000	$2,238,394	$746,131
Johnson	12.000	$4,924,346	$1,641,449
Laramie	12.000	$33,464,623	$11,154,874
Lincoln	12.000	$12,995,833	$4,331,944
Natrona	12.000	$19,239,875	$6,413,292
Niobrara	12.000	$2,072,668	$690,889
Park	12.000	$12,002,605	$4,000,868
Platte	12.000	$3,001,379	$1,000,460
Sheridan	12.000	$8,939,730	$2,979,910
Sublette	12.000	$46,082,196	$15,360,732
Sweetwater	12.000	$31,889,182	$10,629,727
Teton	6.879	$28,254,208	$16,429,253
Uinta	12.000	$5,835,196	$1,945,065
Washakie	12.000	$2,086,157	$695,386
Weston	12.000	$2,334,208	$778,069
Totals	**11.732**	**$354,989,740**	**$127,204,684**

While the Statewide total of $127 million that could potentially be raised here significantly exceeds the estimated ~$30 million annual subsidy gap for EMS, it's important to note the following:

[20] Senate Enrolled Act 38, now Chapter 72 of the 2023 Session Laws.

[21] Wyoming Department of Revenue, 2024 Annual Report, page 21. https://drive.google.com/file/d/1xxPuPeKg_4nD_ktvC7rUMdX3gunLXwCU/view

- **Voters are reluctant to tax themselves.** When the only existing EMS District in Wyoming (Glendo) put the mill levy on the ballot in May of this year, the question failed 33 to 119.[22]
- **The amount raised per mill varies significantly by county.**[23] Many of the counties that *could* raise significant revenue through an EMS district likely do not *need* to, either because they already have well-funded services (Jackson) or because EMS service revenue already sufficiently covers the cost of readiness (Laramie, Campbell, Natrona, Sheridan). Conversely, the smaller, more rural counties (Niobrara, Weston, Crook, Big Horn, etc.) that likely *need* the subsidy the most wouldn't be able to cover as much with the levy.

4.6.3 Partially implemented: Regionalize and consolidate services

Under this concept, EMS services would merge together on a regional basis to operate in a more coordinated and efficient fashion. Just like the consolidation of school districts, this would likely cut overhead, but it's unclear how much efficiency can be wrung out on the ambulance service level. There will still be rural places with low volume that need an ambulance, so efficiency may come at the expense of quality —or perceived quality.

Interestingly, much of this is already happening due to market forces, without any central planning by the State. Examples in the last few years include:

- Campbell County Health expanding operations to Sheridan and Newcastle;
- Cody Regional expanding operations in the Basin;
- Platte County hospital expanding to Guernsey;
- The Castle Rock hospital district taking over EMS operations in Sweetwater County;
- Torrington EMS expanding in Goshen County; and,
- The consolidation of Alpine and Thayne into Star Valley Health.

4.6.4 Idea: Increase Medicare EMS rates and covered services

While Medi*care* volume is significant for ground EMS (i.e., making up over 40% of calls) and rate increases would make a meaningful difference to services' sustainability, control over the program is entirely federal. The fee schedule and covered services are set by the Centers for Medicare and Medicaid Services (CMS).

This is simply not a lever that's immediately available to State policymakers. However, the State has discussed with its Congressional delegation changes to the program such as:

- **Rate increases** to reflect the cost of care in rural and frontier settings. Because fixed costs have to be spread out over low volume in these settings, average costs per transport are much higher than in denser urban environments.
- Allow EMS agencies to **bill Medicare for responding, not necessarily transporting**, likely at a lower rate. This would allow the ~34% of non-reimbursable Medicare volume to be billed.
- Consider implementing **global payments**, i.e., Medicare paying a flat amount to the State for all transports. This could contain financial risk for Medicare while allowing the State to fine-tune

[22] https://www.plattecountywyoming.com/media/Elections/Election%20Results/2025/Glendo%20EMS%20District/Official%20Results.pdf

[23] E.g., correlating with mineral wealth, property values and population density.

how Medicare revenue is distributed (e.g., pay smaller services for their reasonable fixed costs.)

4.6.5 Partially implemented: Increase Medicaid EMS rates and covered services

Wyoming does have direct control over Medi*caid*, through the Department of Health.

We have, for example, expanded services like "treat and release" where EMS personnel can show up to a call and provide care, without transporting patients to a hospital or emergency room. Medicaid also covers scheduled clinical services provided by EMS personnel, when directed by a physician. Both services are ways for ambulance services to use their personnel and draw down revenue outside 911 calls and inter-facility transports. Utilization of both services, however, is very low.[24]

Similarly, Medicaid rates can be increased, within limits. While this would certainly help ground EMS services, particularly if the rate for dual-eligibles was set to Medicare levels,[25] there are some caveats:

- Medicaid EMS market share is relatively low,[26] so the impact of a Medicaid rate increase on provider revenue is much lower than a Medicare rate increase.
- Rate increases benefit higher-volume EMS agencies the most. They don't solve the fundamental problem for smaller agencies: fixed readiness costs can't be covered by service volume.
- Any rate increase requires Legislative appropriation. In SFY 24, for example Medicaid paid $1,483,894 for ground EMS claims. Half of this amount is State General Funds (SGF).

4.6.6 Implemented: Establish a Medicaid Upper Payment Limit (UPL) program

UPL programs are a not-uncontroversial method of funneling additional federal dollars to Medicaid providers without additional SGF. As noted in the previous section, most Medicaid expenditures in Wyoming are a 50-50 match of State General Fund and Federal Funds. UPL programs essentially use provider funds as the State match. Here's an example:

- Pretend you are an ambulance service.
- I, the State, impose a provider tax on ambulance revenue, not to exceed 6%.
- You pay me taxes of $1.
- I take that dollar and use it to draw down a federal dollar, with the logic that I will increase your overall Medicaid rate up to what Medicare *would have paid* for the ambulance services you've rendered.[27]
- Now the State has two dollars, which I turn around and give back to you.
- On net, you have one more dollar than you had before.

The reality is slightly more complicated, but this toy example shows why both States and Medicaid providers find this arrangement attractive.

The Legislature has directed Wyoming Medicaid to set up multiple UPL programs in the past, to include:

[24] In SFY2023, Medicaid paid out a total of $3,420.25 in claims for both types of community paramedicine.

[25] Under current 'lesser of' logic, Medicaid does not pay the cost-sharing component for Medicare claims for dual-eligibles because the base Medicare rate already exceeds what Medicaid would have paid. This policy was implemented as a budget cut circa 2018.

[26] Most Medicaid members are children, whose risk of ambulance transport is much lower than older adults.

[27] This is what the term "Upper Payment Limit" refers to.

- Nursing homes;[28]
- Hospitals;[29]
- Psychiatric residential treatment facilities;[30] and,
- Hospital-owned physicians[31]

For ambulances, the UPL program was implemented during the last fiscal year, with claims approved retroactively back to July 1st, 2023.[32] In SFY 2024, the UPL netted ground EMS providers $1,472,889 in additional federal funds. This increased to $1,709,827 in SFY 2025. The UPL program is therefore effectively *doubling* Medicaid ambulance payments using federal funds alone.

[28] W.S. 42-8-101 through 109, start date 4/1/2011, as well as the "Gap" program in W.S. 42-4-104, start date 7/1/2016. Both net ~$16.5M in FF per year.

[29] W.S. 42-4-104 for public hospitals, start date 7/1/2003; W.S. 42-9-104 for private hospitals, start date 7/1/2016. Both net ~$36M in FF per year.

[30] W.S. 42-9-102(xi), start date 7/1/2023. This program nets ~$4M per year.

[31] W.S. 42-9-101 and 104, start date 7/1/2020. This program nets $11.2M per year.

[32] W.S. 42-11-101 through 109.

5 Recommendation

All of the options in the previous section can still be pursued or further developed, but we suggest a new idea here: using State-funded incentives to nudge county and local governments to adopt the most effective and efficient funding solution that works for them.[33]

While each local area faces a unique situation, these solutions will probably rely on a combination of two policies:

- Maximizing service revenue collected; and,
- Leveraging existing entities like hospitals and fire departments to cross-subsidize EMS where service volume can't pay the bills.

We discuss both policies in the next two subsections.

5.1 Maximize billing for services

This means ensuring all calls are billed, and all bills are collected, to the extent practicable and in the most efficient manner, *before* tax dollars and other subsidies are used to fill the gap.

5.1.1 State role: consolidated billing using existing data

While most EMS agencies already bill, the overhead involved can be a significant lift, particularly for smaller services.

Our proposal here is to explore the use of a competitively-procured billing contractor who would use *existing data* in the Wyoming Ambulance Trip Reporting System (WATRS) to generate health insurance claims, submit them to payers, collect on the bills, and then remit revenue back to participating EMS agencies.

If successful, this would:

- **Cut administrative costs** by de-duplicating work of EMS agencies reporting to WATRS and then having to generate bills;
- **Obtain more competitive pricing** for billing services through volume, compared with smaller services trying to procure this themselves;
- **Lower barriers to entry** for entities like fire departments that do not currently bill for services (or even have this administrative overhead); and,
- **Improve the data quality** of WATRS. Since complete and accurate information will be necessary to bill, there are strong incentives for participating entities to be thorough in their WATRS reports.

[33] This option lies between "giving a man a fish" and "teaching a man how to fish," and is something like "giving a man fish based on how many fish he has already caught, thereby encouraging him to take fishing lessons."

Because this system would be voluntary for EMS agencies, the State does face a "chicken/egg"[34] problem. To address this, we would consider including other Department of Health provided services[35] in the contract as a "base" level of billing volume to provide more certainty on the costs required. This would then let us ramp up EMS volume as those services choose.

If the State moves in this direction, it may raise some additional considerations for elected officials:

- How should *balance billing* be handled? Should the State attempt to protect consumers by limiting the practice, or should the State use its authority and administrative infrastructure to "double-down" on collections by, for example, garnishing wages? The State could also do both —be firm on collections, but limit people's bills to a reasonable amount.
- Similarly, should the State use its authority to *require non-ERISA private insurers* plans to be "in network" with this entity and pay some minimum rate? This could provide a significant incentive for EMS services to join the program, while protecting consumers.
- How should *administrative costs* be allocated? Should the State subsidize these, or take a proportional cut from the EMS service revenue stream?

5.2 Leverage Critical Access Hospitals and fire departments in operating EMS

Existing hospitals and fire departments usually have a base of funding, either through taxes or other revenue, that could be used to cross-subsidize the cost of readiness for EMS.

This funding exists simply because both entities *already provide* other critical readiness services to their local communities, like emergency rooms and putting out fires. As with EMS calls, the volume for these services is sporadic, and we pay for the capacity. Large fire departments have an annual budget; they aren't paid on a "per fire" basis.

As most of the cost of readiness here is also labor, the main cross-subsidy of EMS would happen by using the *same personnel* in *multiple roles*; i.e., you train firefighers, hospital nurses and techs as EMTs, AEMTs, and paramedics. Or vice versa.

A secondary subsidy would come from the perquisite of Critical Access Hospitals (CAHs) to be able to bill all *reasonable ambulance costs* to Medicare, if they are the only ambulance service within 35 miles.[36] Because Medicare makes up 40-50% of the payer mix, being able to receive significant additional revenue over the usual Medicare fee schedule is a big advantage.

The 35-mile restriction also implies that preference for these transports should be given to Critical Access Hospitals (CAHs). If no CAH is available, a full-time fire department would be the next best option, purely from the perspective of long-term sustainability.

One of these two options is available in most communities. Table 2, for example, shows the list of towns with Critical Access Hospitals. Larger cities without CAHs tend to have full-time fire departments.[37]

[34] Chicken: How does the State procure billing without knowing the potential volume of service to price? Egg: How would EMS agencies decide whether to participate without knowing the costs and benefits? This is also known as a "first mover" problem.

[35] E.g. patient-days at our five safety-net facilities, Public Health Laboratory testing volume, Public Health Nursing services.

[36] https://www.hrsa.gov/sites/default/files/hrsa/opa/critical-access-hospital-factsheet.pdf

[37] Cheyenne, Casper, Laramie, Gillette, Sheridan, Rawlins, and Jackson.

The major exception to this would be Fremont and Uinta counties, which only have non-CAH hospitals and volunteer fire departments.

Table 2: Critical Access Hospitals (CAHs) in Wyoming

Critical Access Hospital	City
Sweetwater County	Rock Springs
Star Valley	Afton
South Big Horn	Basin
Johnson County	Buffalo
West Park Hospital	Cody
Converse County	Douglas
South Lincoln	Kemmerer
North Big Horn	Lovell
Niobrara Community	Lusk
Weston County	Newcastle
Powell Valley	Powell
Carbon County Memorial	Rawlins
Crook County	Sundance
Hot Springs County	Thermopolis
Torrington Community	Torrington
Platte County	Wheatland
Washakie Medical Center	Worland
North Platte Medical Center	Saratoga
Sublette County	Pinedale

We gloss over the significant cultural, technical, and adaptation challenges to implementing combined fire/EMS or hospital-based EMS models here, but the reality is that many services in Wyoming —and thousands of other services across the nation —have figured out how to make both work.

In fact, as Table 3 shows, most EMS agencies nationally are already fire-department based.[38]

[38] "Medicare Ground Ambulance Data Collection System (GADCS) Report - Year 1 and Year 2 Cohort Analysis." RAND Health Care. PR-A2743-7. https://www.cms.gov/files/document/medicare-ground-ambulance-data-collection-system-gadcs-report-year-1-and-year-2-cohort-analysis.pdf

Table 3: Ground ambulance organization types

Category	Percent
Fire department	41.4%
Private independent EMS	29.4%
Government stand-alone EMS	17.9%
Hospital-based EMS	9.0%
Other	1.5%
Police or other public safety	0.8%

Let's take a look at a brief case study illustrating how this specific kind of fire/EMS model could provide efficiencies over the status quo.

5.2.1 Case study: Fire departments and EMS in Cheyenne and Casper

In Wyoming's two largest cities, both full-time fire departments and private ambulance services respond to 911 calls.

Table 4 shows total CY 2023[39] volume for the two major EMS providers in Cheyenne and Casper. Our focus for this section is the total 911 responses, including both reimbursable and non-reimbursable trips (e.g., 'lift assists'), but we include inter-facility transports for situational awareness.

Table 4: CY 2023 EMS volume by type

	EMS provider	
Type	**AMR**	**WMC**
911 transports	7,968	6,244
911 non-reimbursable	4,072	3,942
Total 911	**12,040**	**10,186**
Interfacility transports	1,675	2,505
Total	**13,715**	**12,691**

Table 5 shows total CY 2023 volume for the two major fire departments in the same cities.[40] Note on this table that *actual fires* make up a thankfully small percent of fire department responses (1.9% and 1.6% for Cheyenne and Casper, respectively).

[39] We do this to align with the two fire department public annual reports. The figures for AMR and WMC elsewhere in this report are presented on an SFY basis, so they differ slightly.

[40] Cheyenne Fire Rescue 2023 Annual Report is available here: https://www.cheyennecity.org/files/sharedassets/public/v/1/departments/fire/cheyenne-fire-rescue-2023-annual-report.pdf and the Casper Fire-EMS report is available here: https://sway.cloud.microsoft/vlNzo84PemofoE8s?ref=Link

Table 5: CY 2023 Fire department volume by type

Type	Fire Department	
	Cheyenne FD	**Casper FD**
EMS response	6,410	6,293
Service/good intention	2,504	1,604
Fires	200	141
False alarms	601	424
Other	300	189
Total	**10,016**	**8,651**

So the natural question from the two tables is: how many of these 911 EMS calls are overlapping, i.e., on how many calls did both a fire engine *and* a private ambulance show up to the same call?

Our estimate using WATRS data[41] is 7,529 for Cheyenne and 8,242 for Casper. This is shown in Table 6. From the EMS service providers perspective, this is an overlap of 62.5% and 80.9% of AMR and WMC's total 911 volume, respectively. From the Fire Department's perspective, the same overlap represents 75% and 95% of of their volume.

Table 6: CY 2023 - Overlapped calls

Type	Area	
	Cheyenne	**Casper**
911 transports	5,179	5,476
911 non-reimbursable	2,350	2,766
Total	**7,529**	**8,242**

This significant overlap has a resource cost, estimated in Table 7. The Cheyenne Fire Department, for example, has almost entirely fixed costs of ~$13.1M,[42] and Casper's Fire-EMS is only slightly less costly at $12.2M.[43]

These base costs are funded by the cities' general funds, whose revenues come from sales/use taxes, property taxes, mineral royalties, license and permit fees, and other miscellaneous revenues (e.g., gaming).

On top of this, however, we add the costs of the ambulance services responding to the same 911 calls, which we estimate at around ~ $2.8M in both cities. These costs are borne by the people (read: taxpayers) and the insurance companies who are billed for the transports.

[41] Since fire departments have only recently started using WATRS to report trips, there is only ~ 3 months of data where all providers are reporting consistently from which to extrapolate. To estimate overlap, we assume that reported dispatches for paired providers (e.g. AMR and Cheyenne FD) that occur within five minutes of each other are from the same call.

[42] City of Cheyenne FY25 budget: https://www.cheyennecity.org/files/sharedassets/public/v/1/departments/city-treasurer/adopted-budgets/2025-proposed-budget.pdf

[43] City of Casper FY24 budget: https://cdnsm5-hosted.civiclive.com/UserFiles/Servers/Server_62983/File/Government/Budget/Budgets/FY24%20Adopted%20Budget%20-final.pdf

Table 7: CY 2023 - Estimated 911 response costs

Agency	Est. cost	Funding
AMR	$2,826,877	Medical bills
WMC	$2,779,941	Medical bills
Cheyenne FD	$13,148,226	Cheyenne tax revenue
Casper FD	$12,159,691	Casper tax revenue

For just Cheyenne and Casper, therefore, the reduction of this overlap by "having the fire departments do the EMS" (the devil, of course, being in the details) represents a potential savings of ~$5 million per year.[44] If other cities with full-time fire departments (e.g. Gillette, Rock Springs) were included, this total would increase. These savings could either supplant tax dollars, or support EMS in more rural areas of Laramie and Natrona counties where service volume will never pay the bills.

As noted previously, this kind of transition involves a host of complications. These include potential issues regarding:

- **Quality of care**, from switching away from two high-performing commercial ambulance services (AMR and WMC) to more untested fire departments;
- **Efficiencies being be wasted** if fire departments don't actually use existing staff; i.e., if they build out a completely separate EMS structure;[45]
- **Coverage**, i.e., the question of which agencies will serve the outlying areas of Natrona and Laramie counties if the fire departments only serve the cities of Casper and Cheyenne; and,
- **Cultural differences** and **labor complications** between firefighers and EMTs, union vs. non-union employees, etc.

We can't answer these questions here. We provide this case study merely to show the potential for efficiencies using existing resources, as well as noting that most EMS agencies nationally operate under a combined fire/EMS model, so the complications can hopefully be worked out. Any decision to move in this direction must be undertaken by county and municipal authorities weighing all the costs and benefits involved.

5.2.2 State role: matching funds for more sustainable subsidies

To reiterate, the Department does not want to be in the role of deciding what works most effectively at the local level. However, if the Legislature deemed it appropriate, we could provide incentives, in the form of matching State General Fund dollars, to EMS services that seek out more sustainable subsidies, for example, those that:

- Engage with the potential State consolidated billing system;

[44] Including the loss of the annual revenue received from AMR, but not including transition costs like buying the fire departments ambulances and cross-training their staff.

[45] Anecdotally, this happened in Sheridan a decade or two ago, and costs apparently ballooned when the fire department assumed ambulance service.

- Receive Critical Access Hospital (CAH) cost-based Medicare revenue;
- Use a combined fire/EMS model; or,
- Raise local funds through fundraisers or EMS service districts.

The use of these matching funds would not only direct additional needed revenue into the system, but would also create incentives to move towards business models that are more likely to survive in the long run.

6 EMS volume and risk estimates

Now, we get to the facts and figures. This section begins with background on how EMS volume in Wyoming correlates with demographic factors, before illustrating how it varies over time and space. We try to answer questions like:

- Which age groups use EMS the most?[46]
- Where is EMS volume spread or concentrated in each county?
- Which highways have the most crashes?

Where appropriate, we also try to measure *risk*, i.e., when that call volume is divided by some underlying measure of exposure like "number of people" or "amount of traffic."

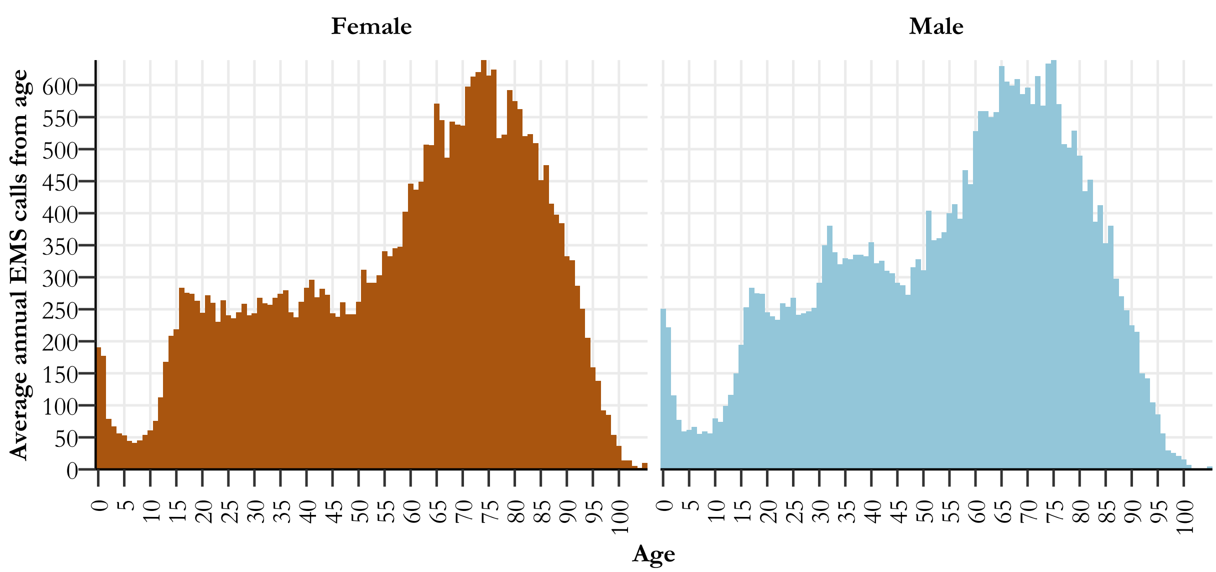
We begin with looking at demographics, then consider within-county geographic volume before concluding with a look at EMS calls on highways.

6.1 Demographic risk

Figure 1 shows how average annual EMS call volume is distributed by age and sex (brown on the left panel showing women, and blue on the right showing men). Within each panel, the height of each thin column shows how many calls were received from people in that 1-year age group.

75-year old women in Wyoming, for example generated an average ~ 650 calls per year, compared with 6-year old boys, who had around 50.

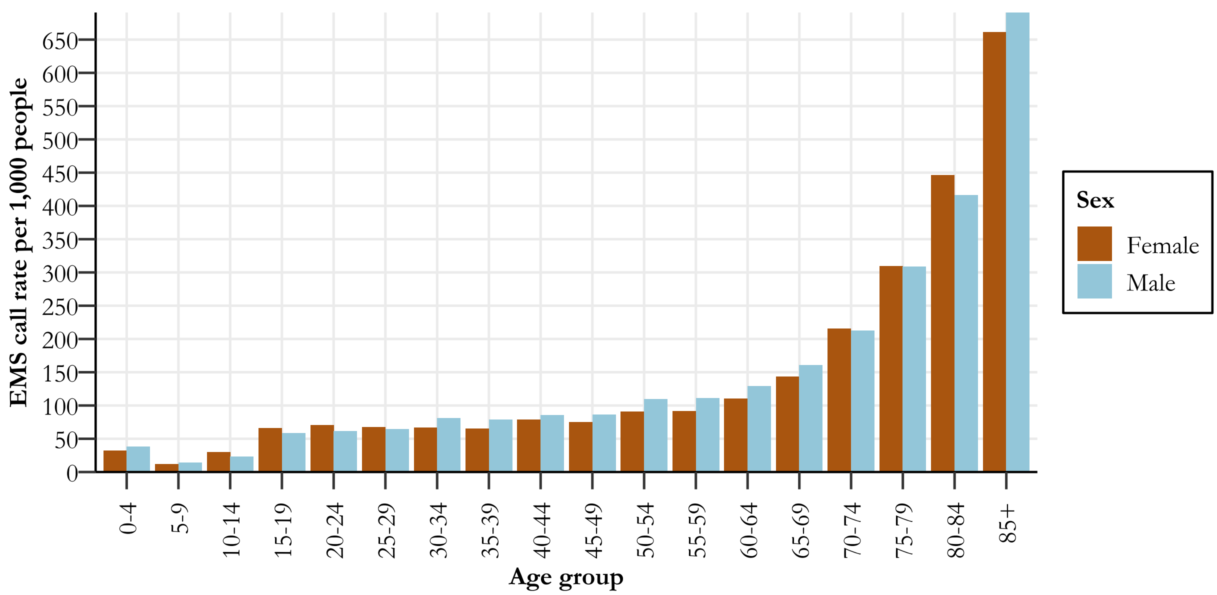
Figure 1: Average annual EMS call volume by single-year age group



[46]Spoiler alert: as trauma risk increases exponentially with age, over 40% of EMS volume comes from those over 65.

When these counts are divided by the total number of people in each demographic group,[47] we can illustrate the *rate* of EMS calls per 1,000 people on Figure 2.

Figure 2: EMS call rates per 1,000 people by demographic



Taken together, the figures reflect some stylized facts:

- The *rate* of EMS calls mirrors the usual "J-curve" of health utilization, and risk of death generally.[48] Newborns have moderate risk, kids have the lowest, and then risk begins rising over adulthood — slowly at first, and then more dramatically after 60.
- Generally speaking, around 40% of total EMS volume comes from people who are over 65. Medicare is thus a major payer for these services.
- Utilization differs slightly between women and men. 15-29 year old women generate slightly more calls than their male counterparts (potentially due to childbirth), but the dynamic flips for 30-50 year old men.[49]

[47] We use 2020 Census data for 5-year age/sex/race groups and census blocks

[48] https://ourworldindata.org/how-do-the-risks-of-death-change-as-people-age

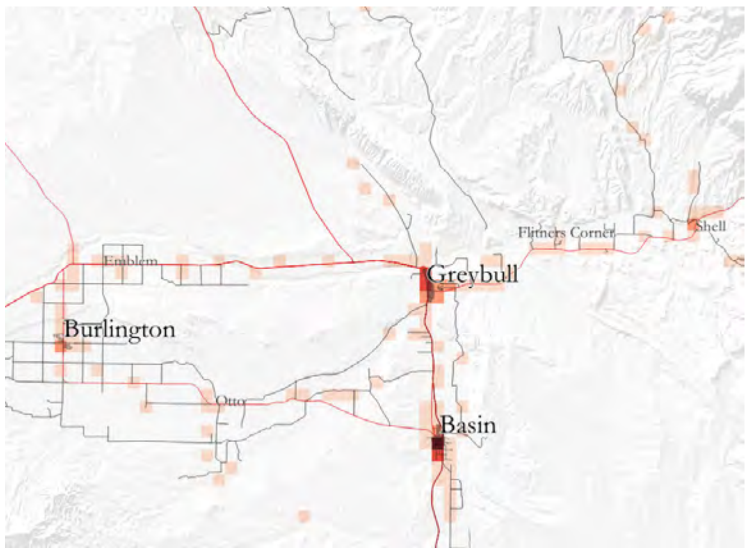
[49] We present this observation without comment: "Men were significantly more likely than women to have injuries related to all-terrain vehicle accidents, motorcycle accidents, RV accidents, burns, gunshot wounds, and stab wounds. Men were significantly more likely than women to have illnesses related to cardiac arrest, dead on arrivals (DOAs), drowning, and smoke inhalation." from Weiss SJ, Ernst AA, Phillips J, Hill B. Gender differences in state-wide EMS transports. Am J Emerg Med. 2000 Oct;18(6):666-70. doi: 10.1053/ajem.2000.16299. PMID: 11043618.

6.2 Geographic risk

Now, let's look at how the volume of EMS calls is distributed geographically.

Instead of grouping calls by age and sex groups, we divide Wyoming into ~260,000 grid squares —each 1 x 1 km —and count the number of EMS calls originating from that square in the 3 years from SFYs 2022 through 2024.

Figure 3: EMS volume around Basin



We then divide that number by three (3) to get an average annual count, and then classify that count into four major categories on the map:

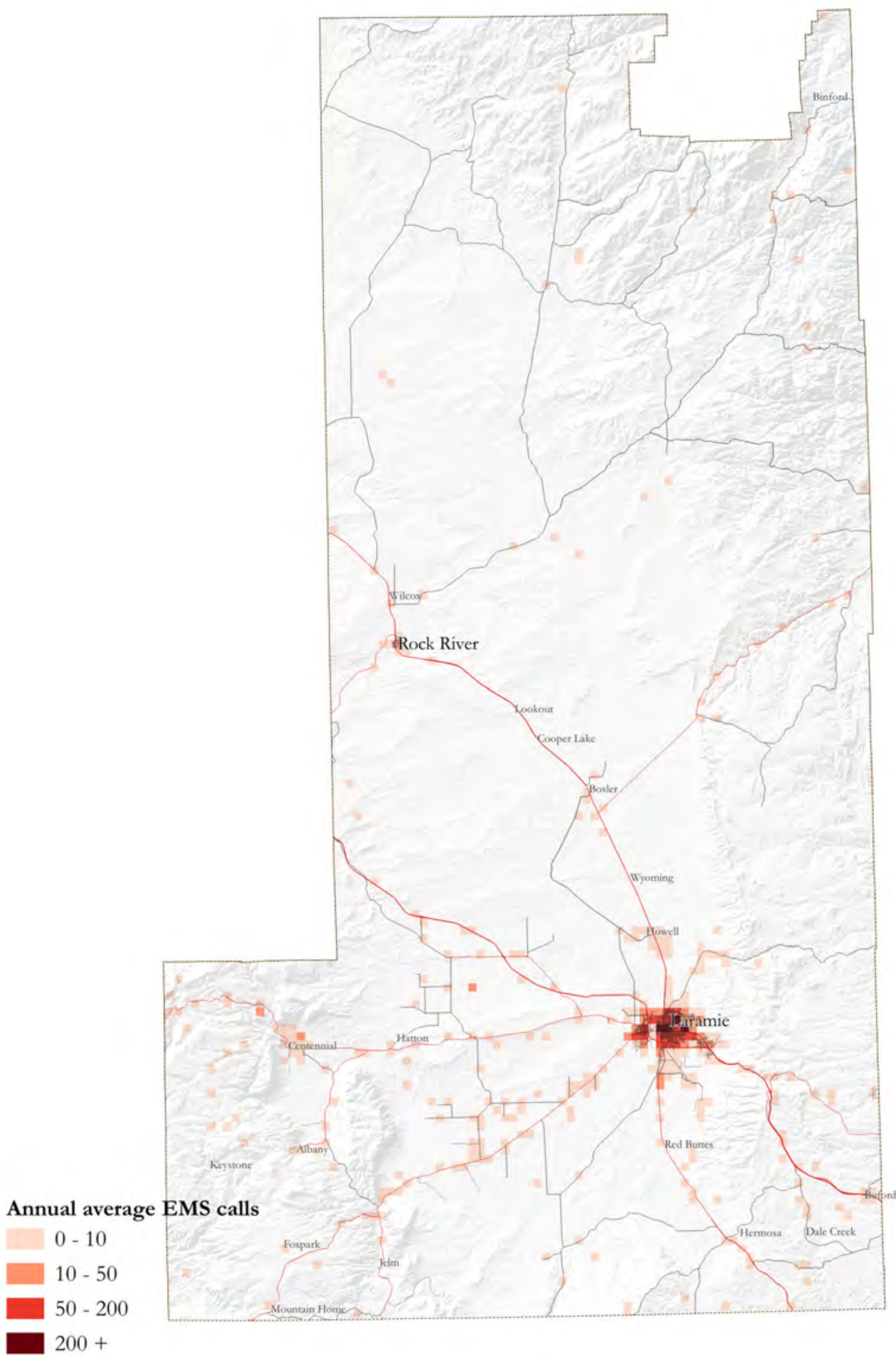
- 0 to 10 calls (beige);
- 10 to 50 calls (orange);
- 50 to 200 calls (red);
- 200+ calls (dark brown).

In the example shown in Figure 3, note that EMS volume correlates with population density. Greybull and Basin have more volume than Shell or Flitner's Corner, simply because more people live there.

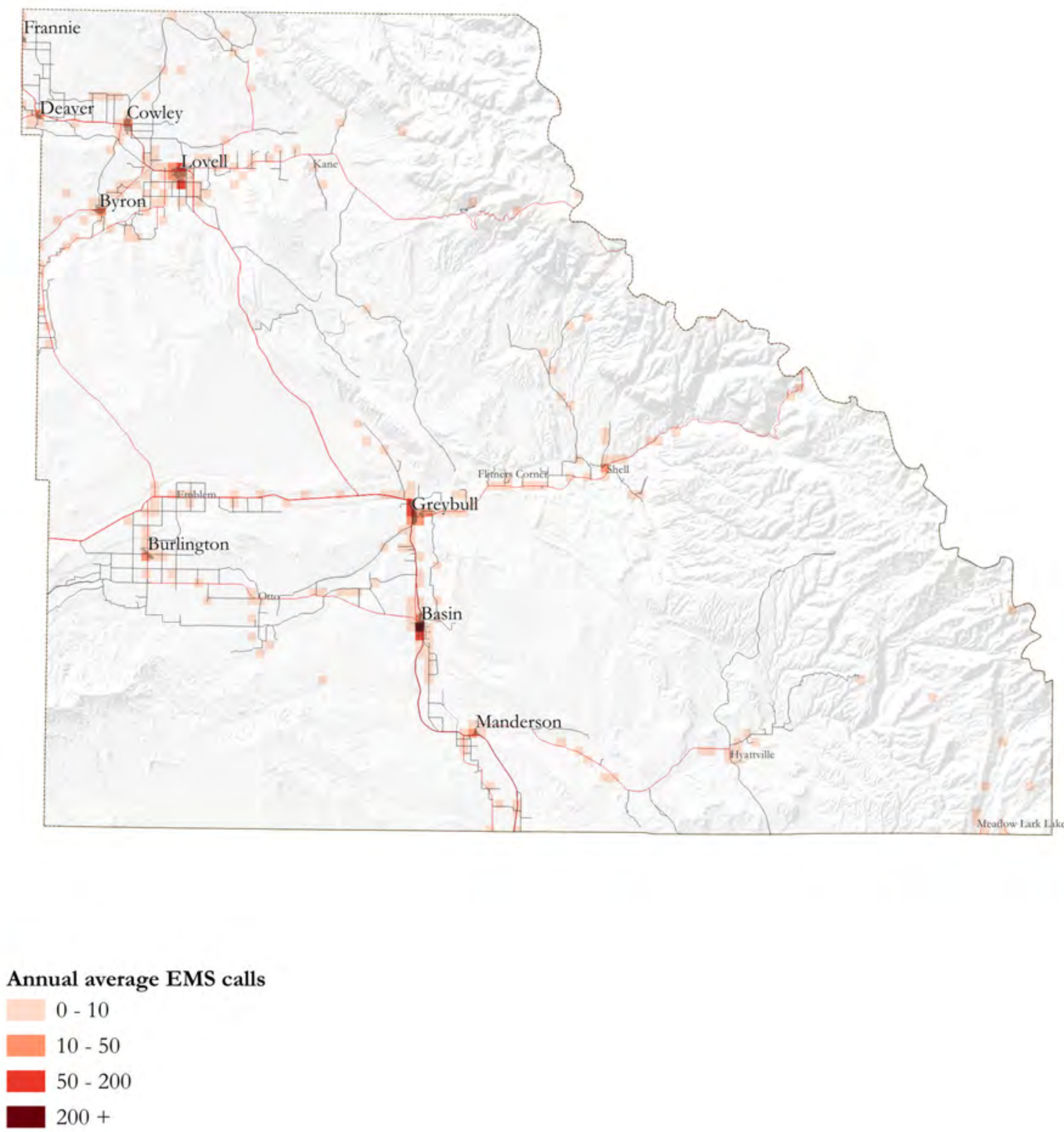
Because EMS demand increases with age, however, and because the data includes calls like inter-facility (e.g. hospital to hospital) transports, grid squares that include hospitals and nursing homes do show disproportionately higher volume.

To provide granular detail at this scale, we look at each county individually on its own page.

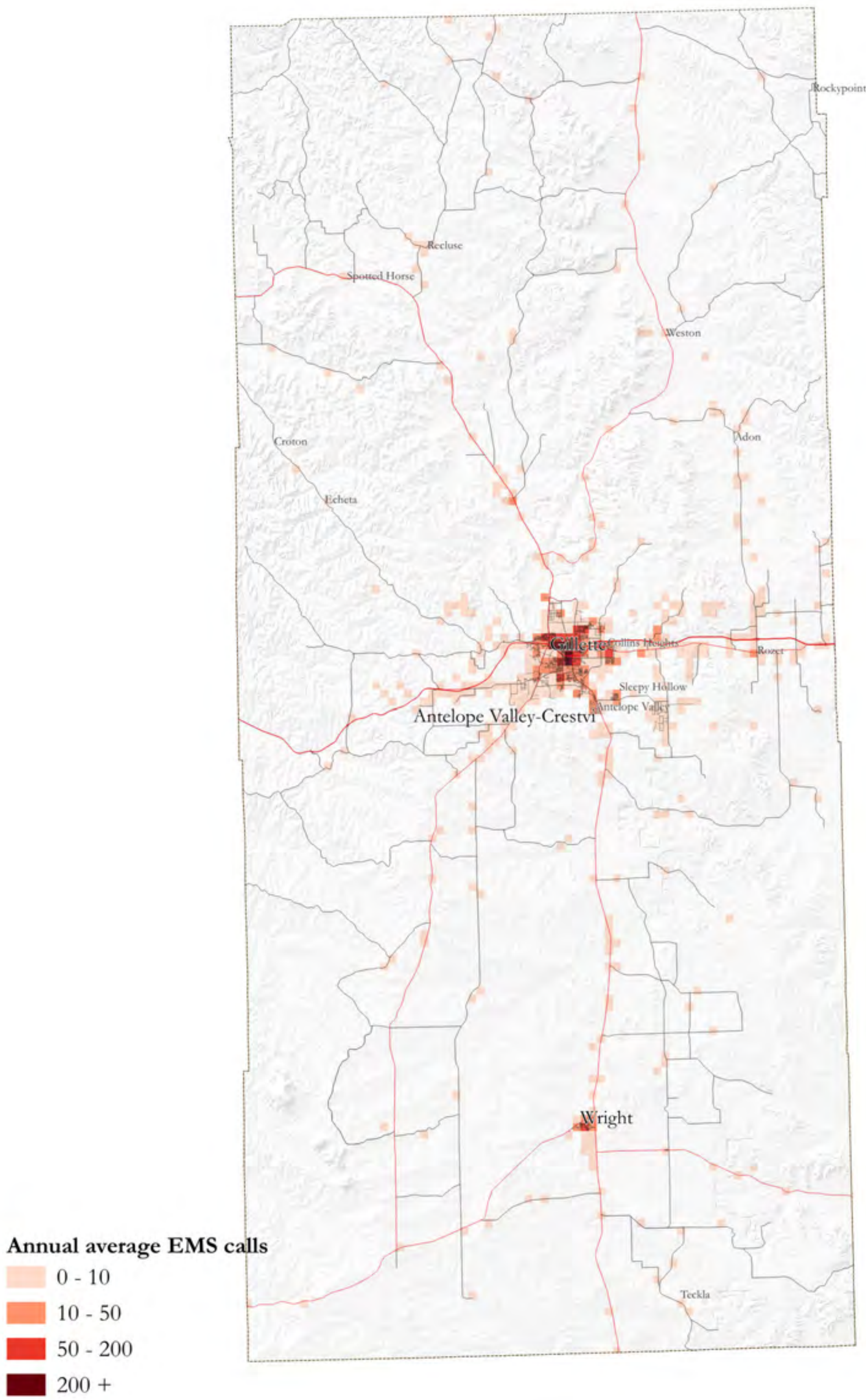
6.2.1 Albany County



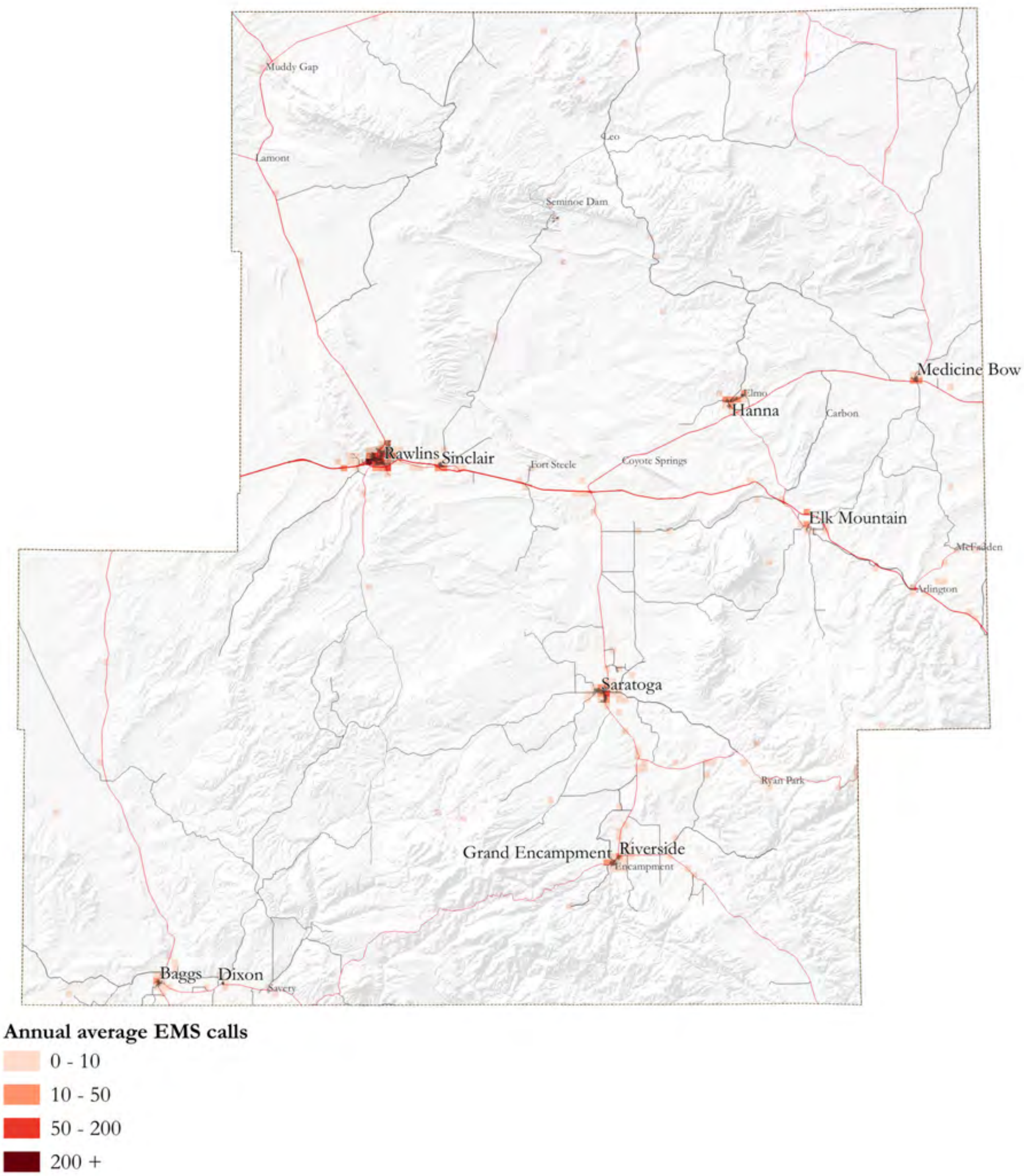
6.2.2 Big Horn County



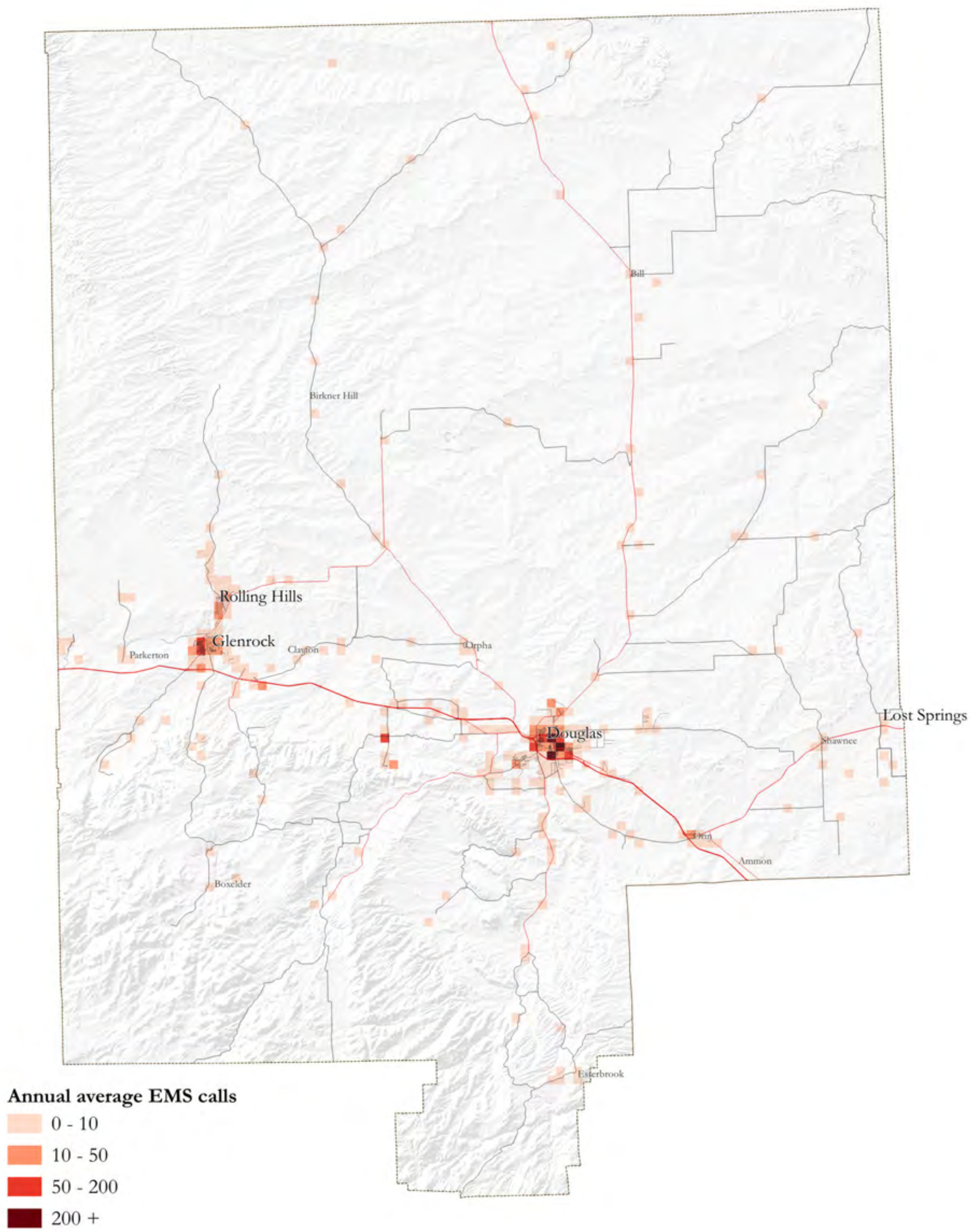
6.2.3 Campbell County



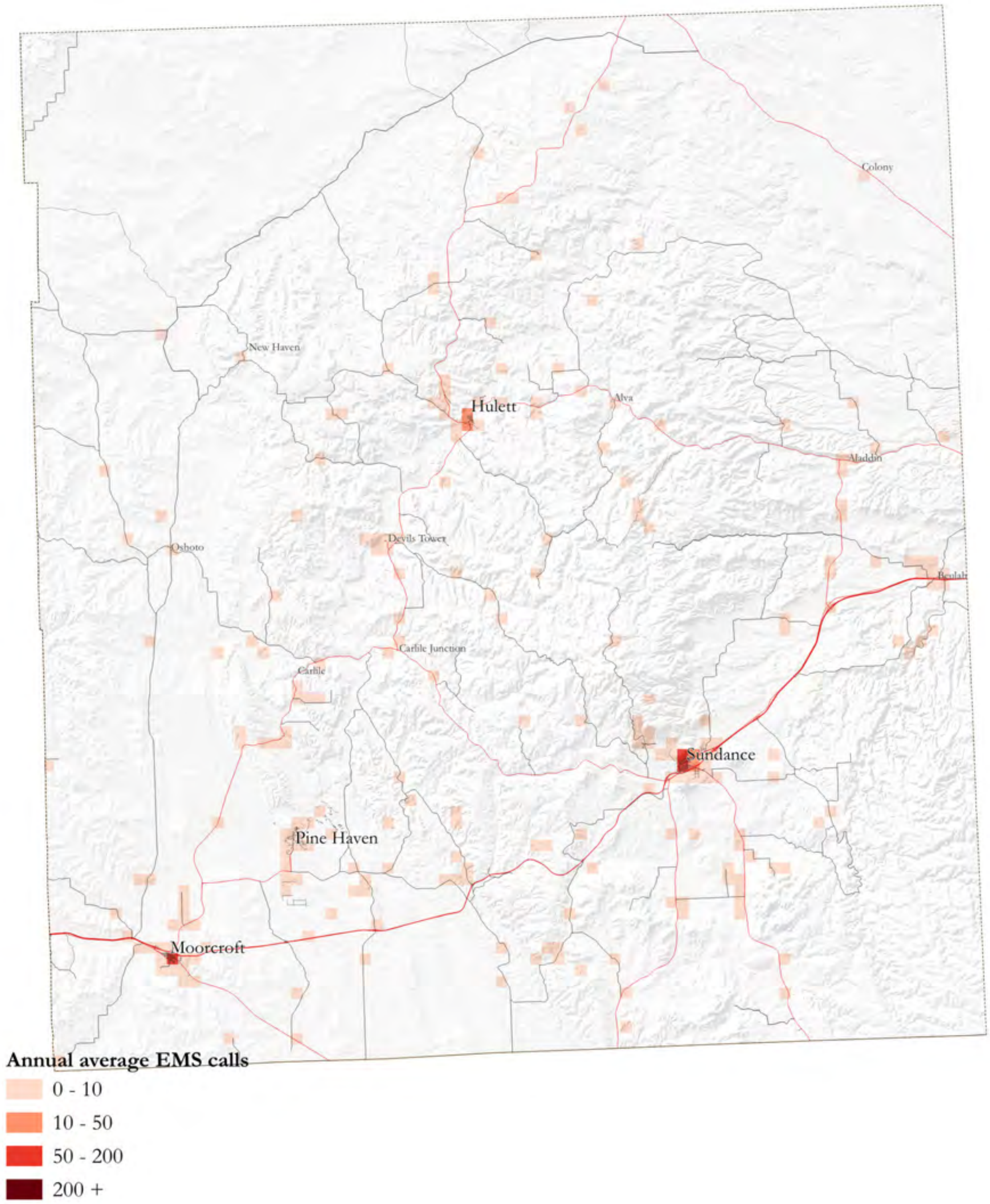
6.2.4 Carbon County



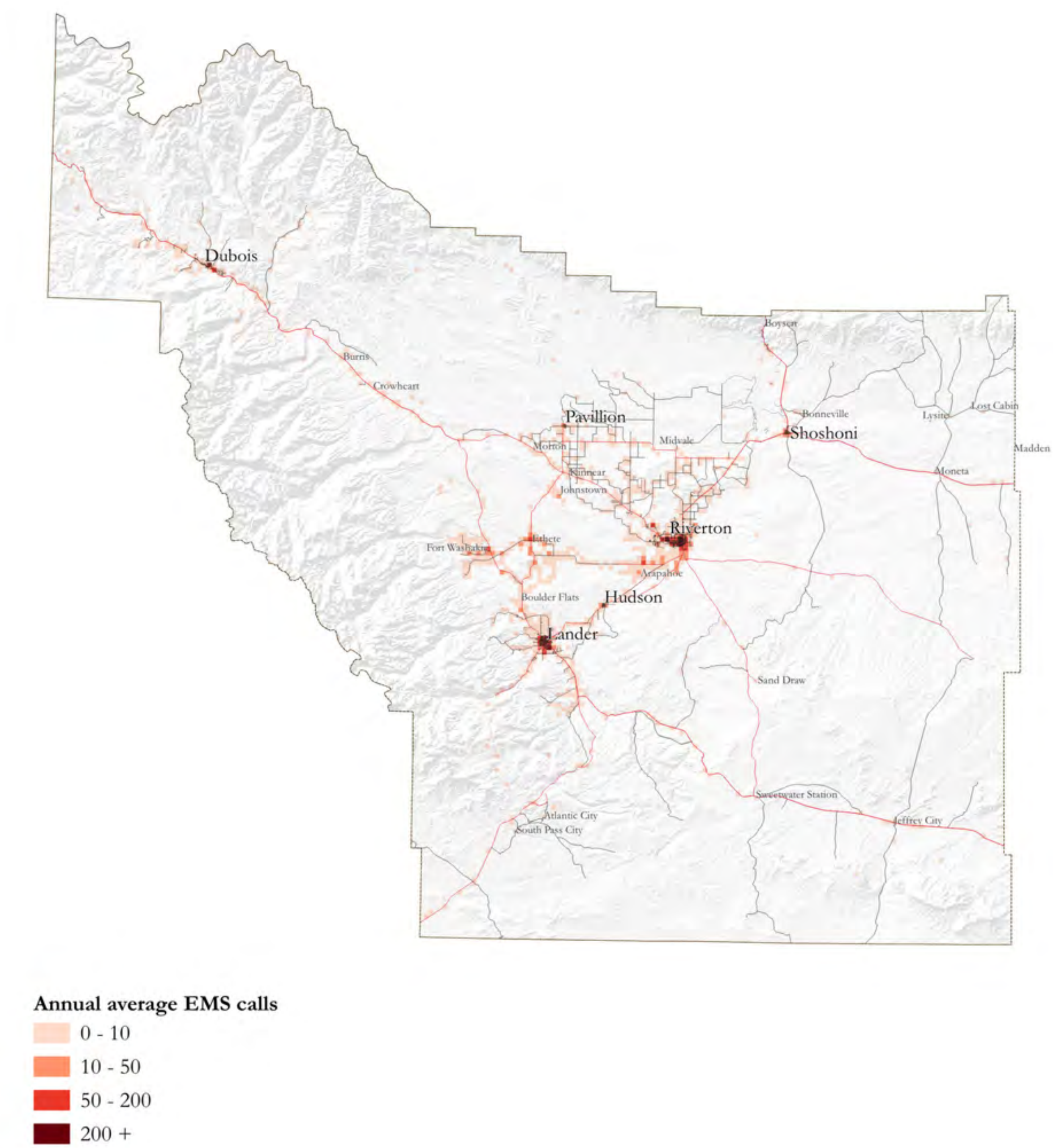
6.2.5 Converse County



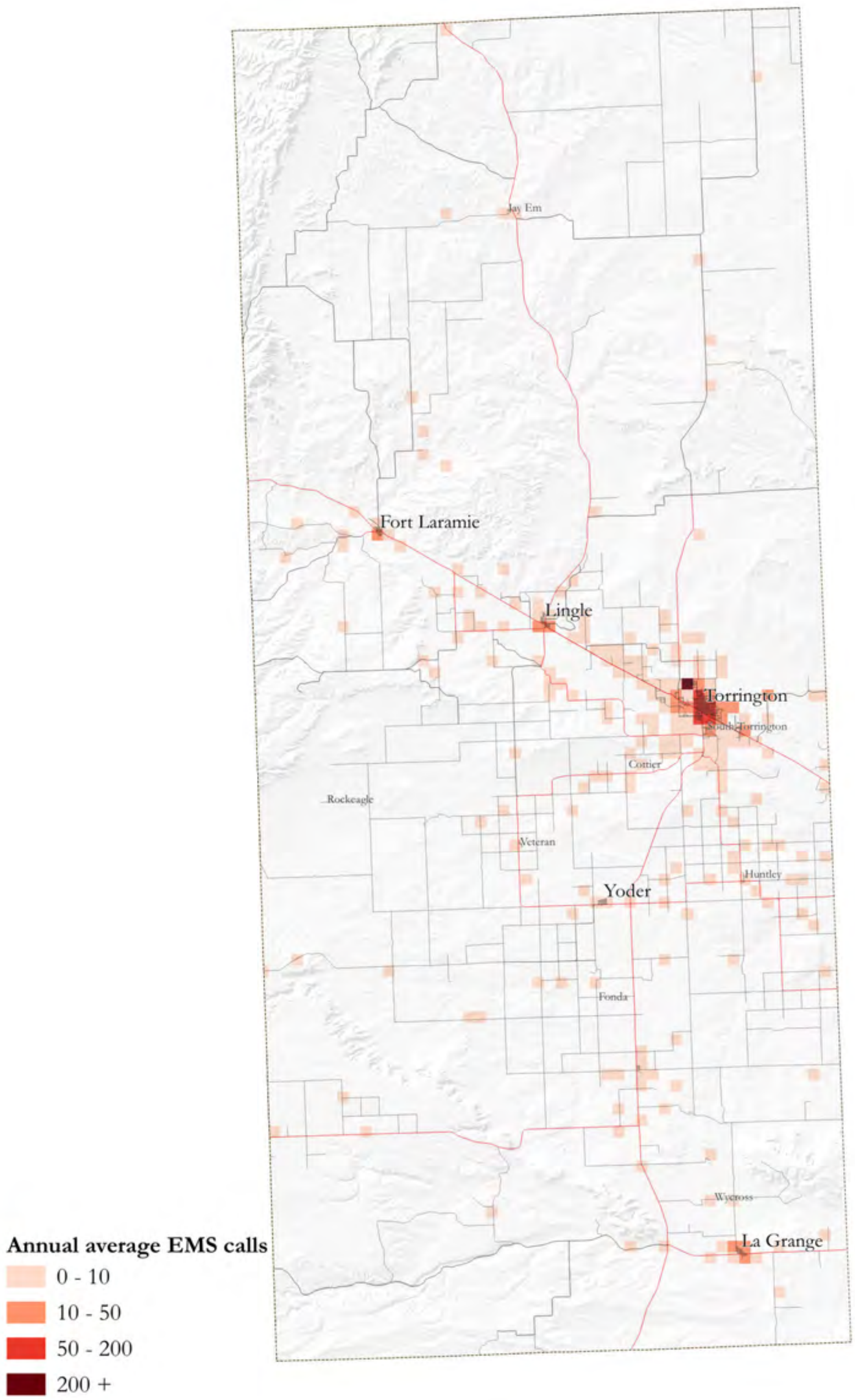
6.2.6 Crook County



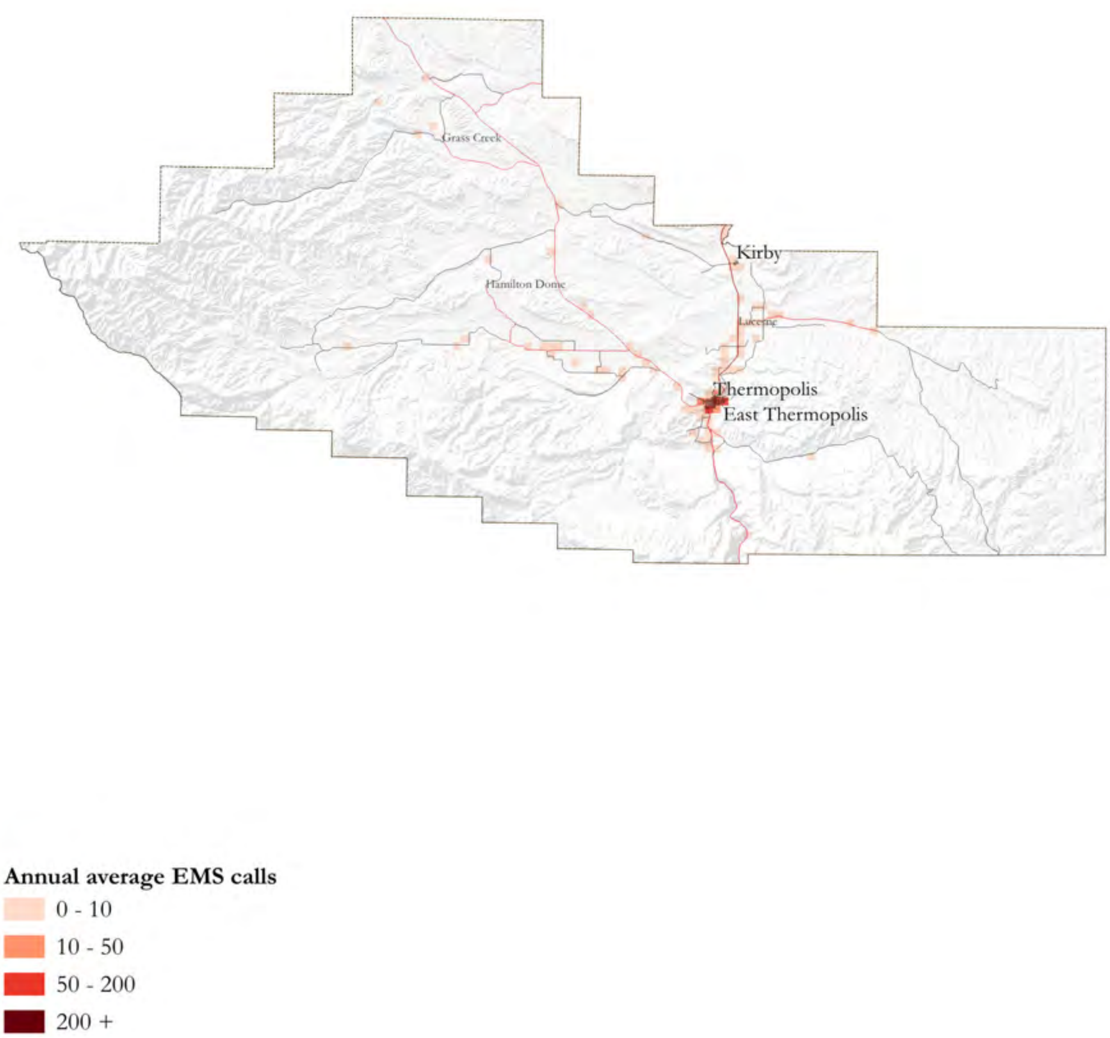
6.2.7 Fremont County



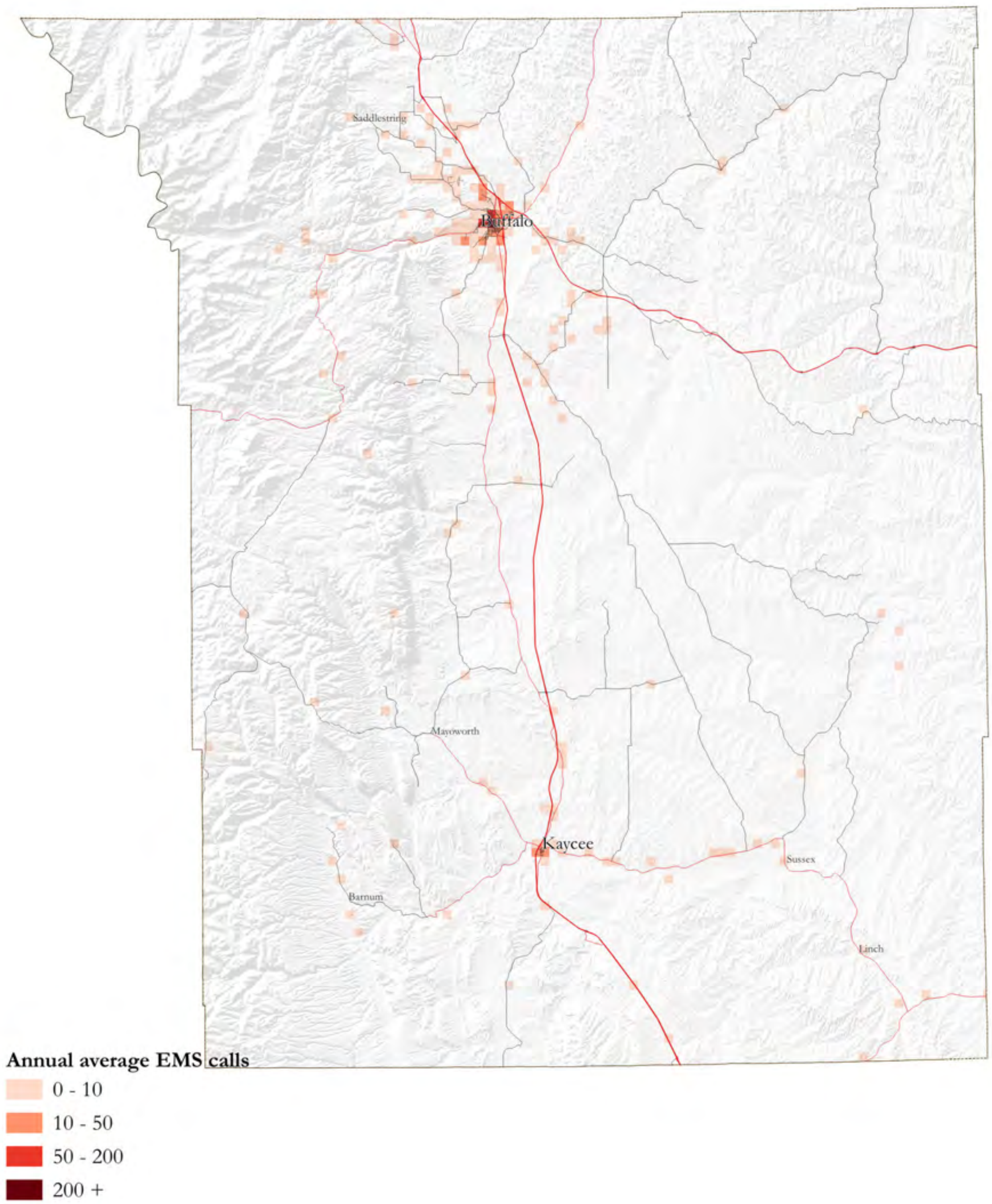
6.2.8 Goshen County



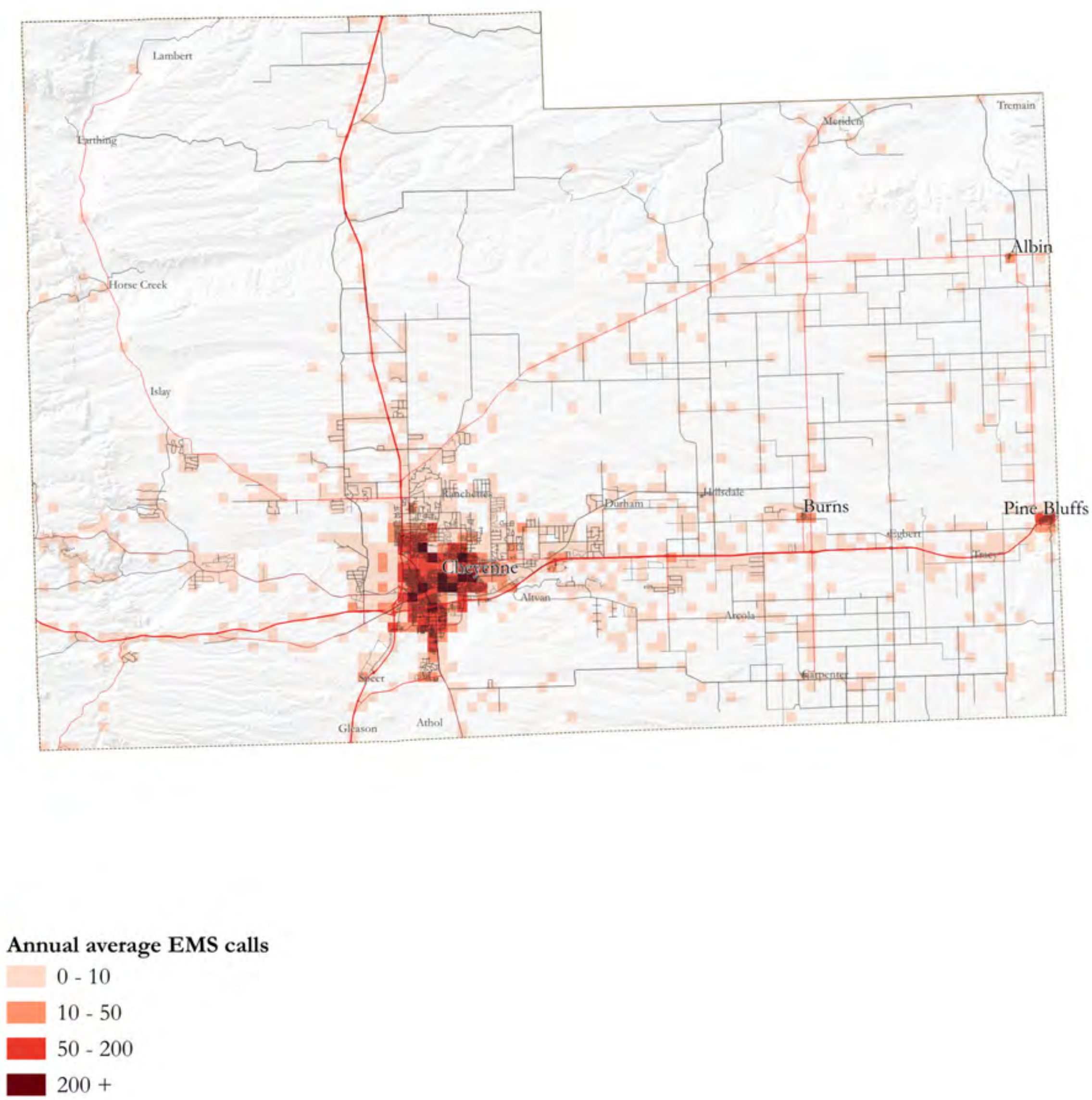
6.2.9 Hot Springs County



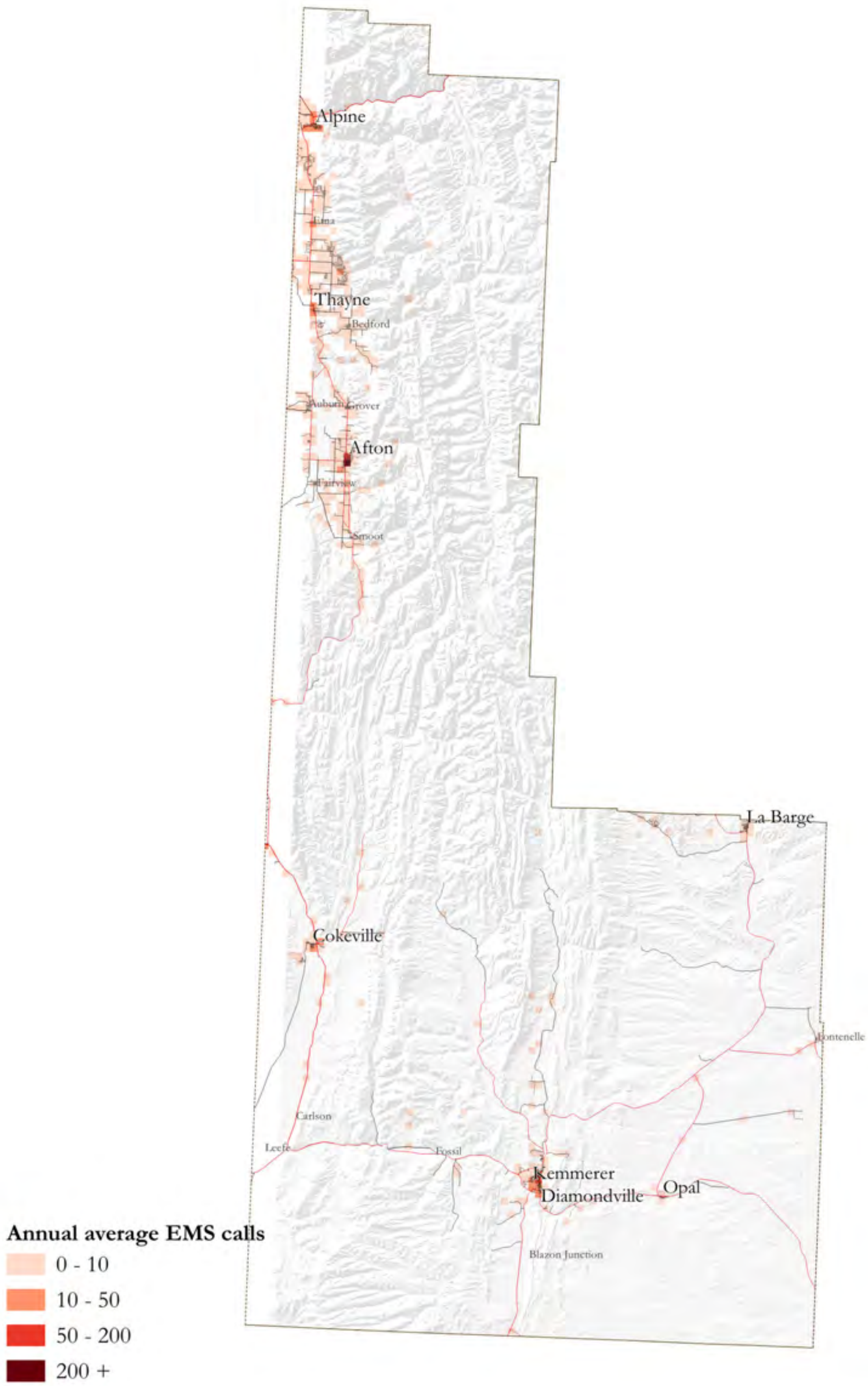
6.2.10 Johnson County



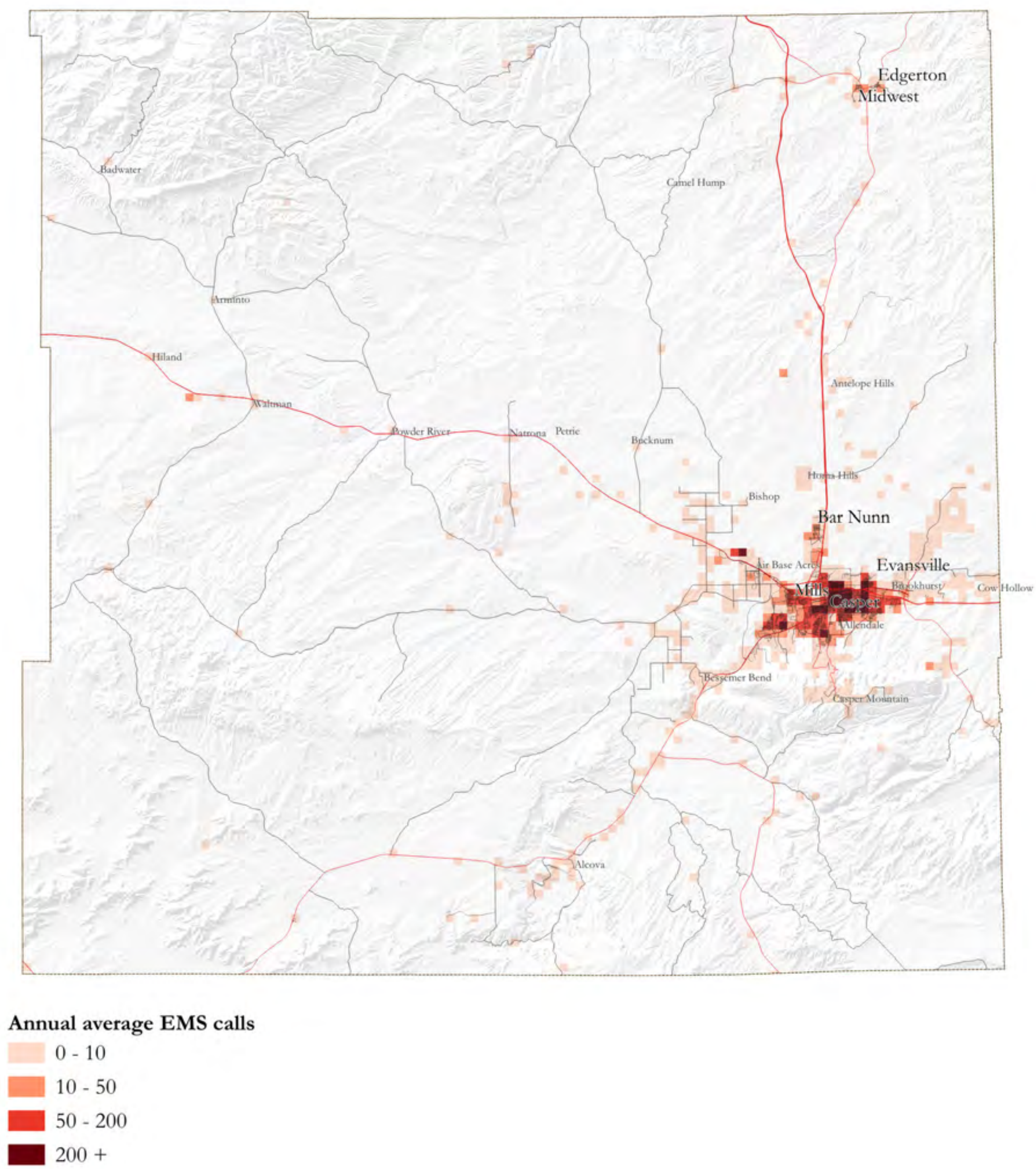
6.2.11 Laramie County



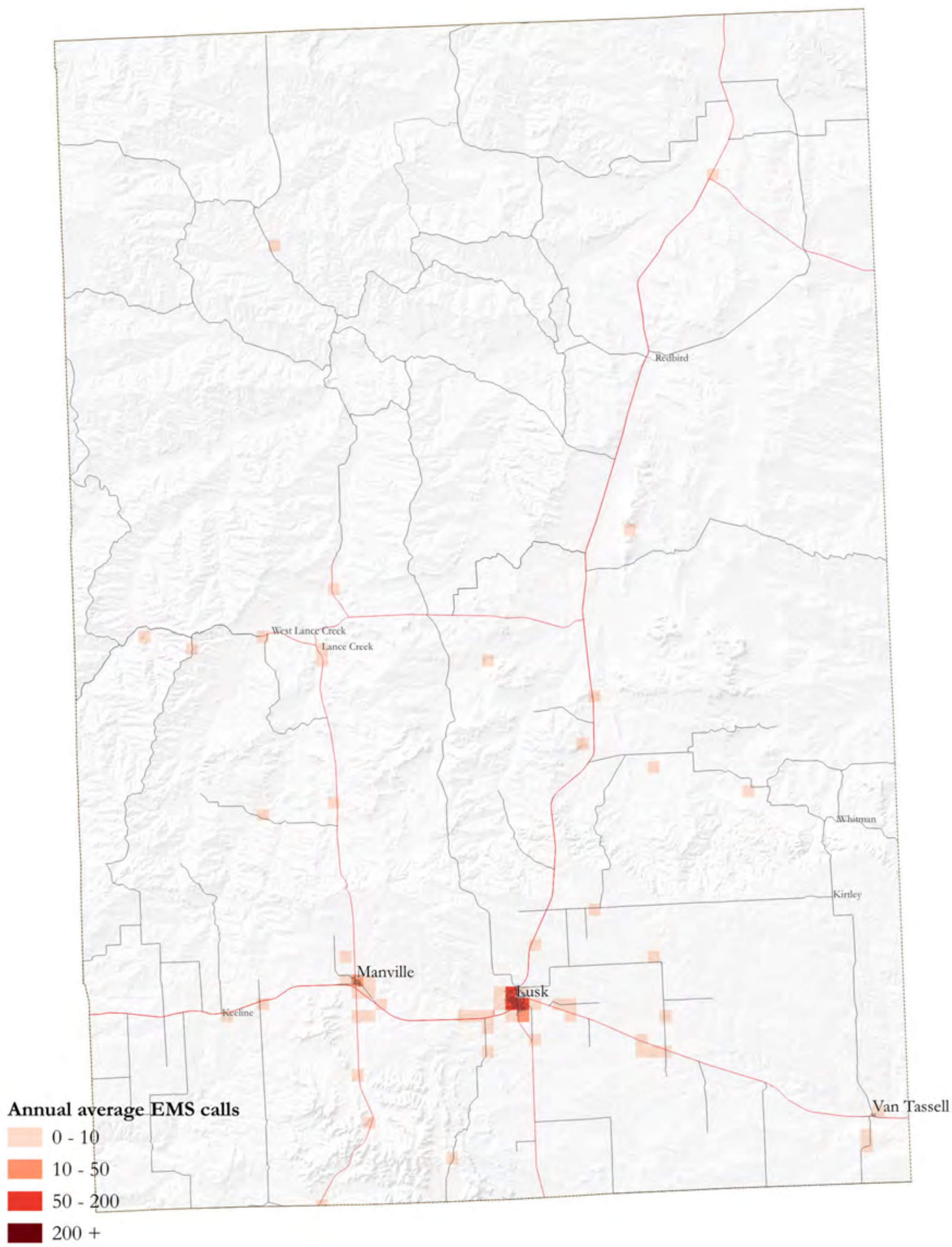
6.2.12 Lincoln County



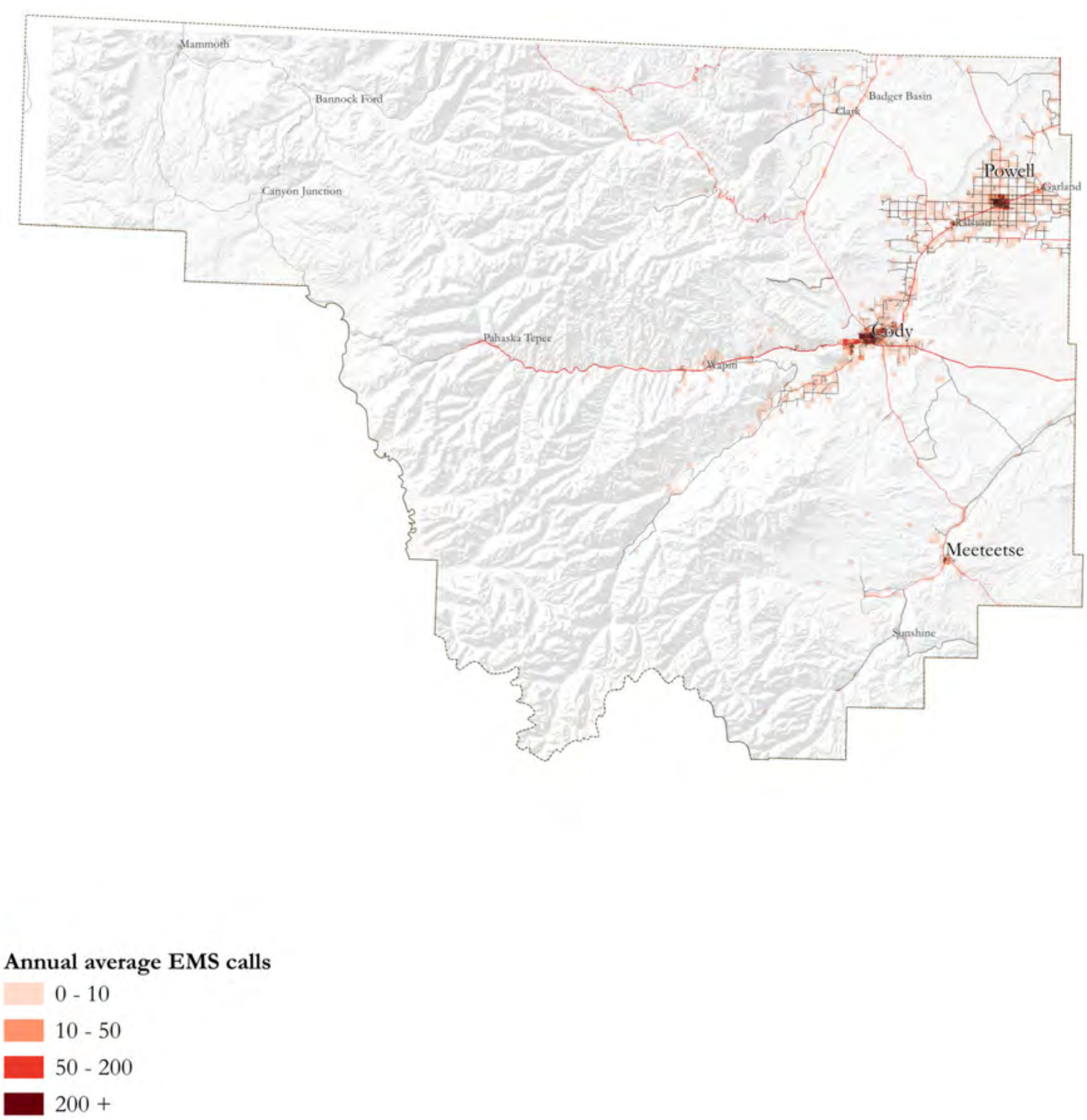
6.2.13 Natrona County



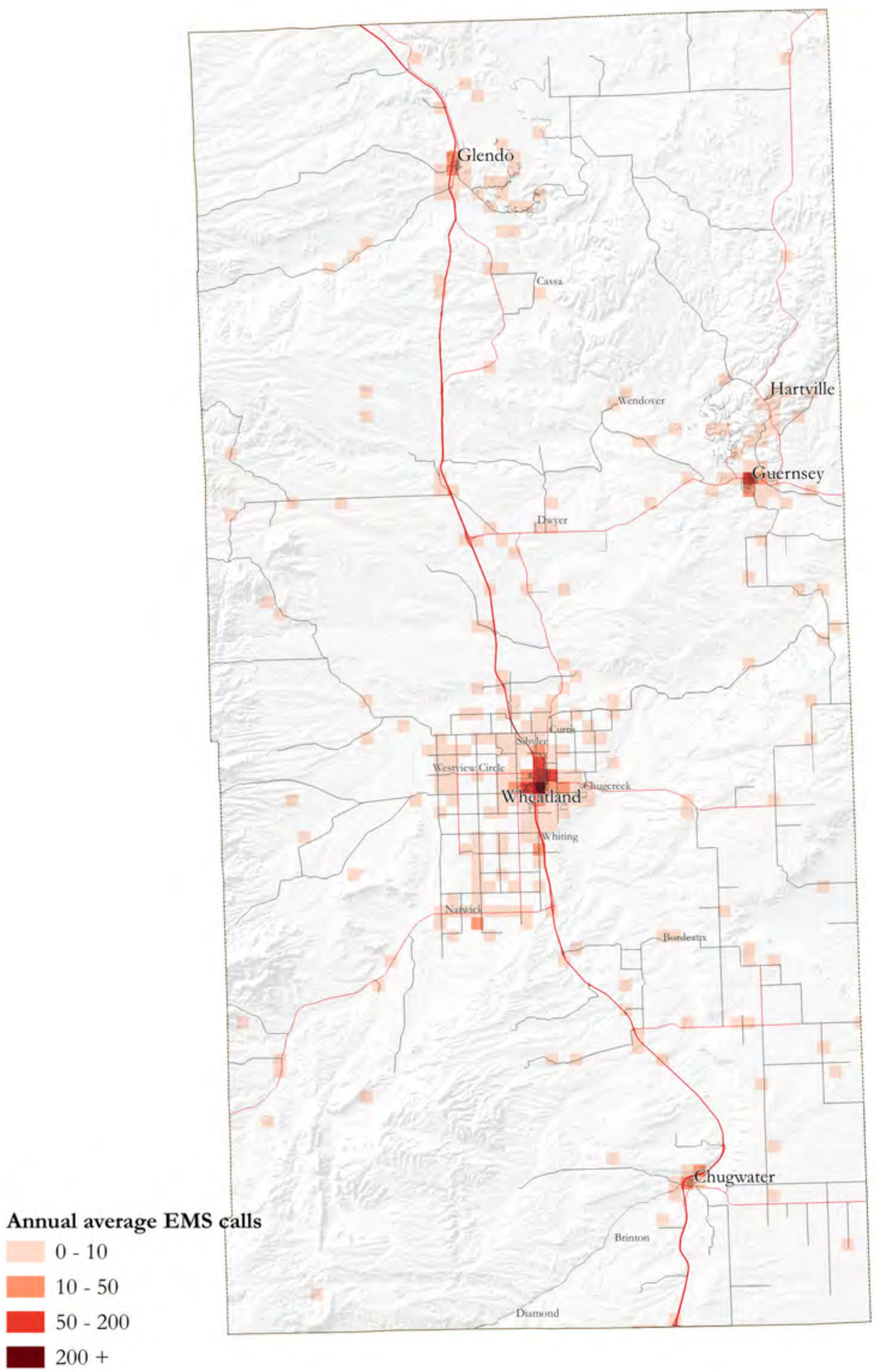
6.2.14 Niobrara County



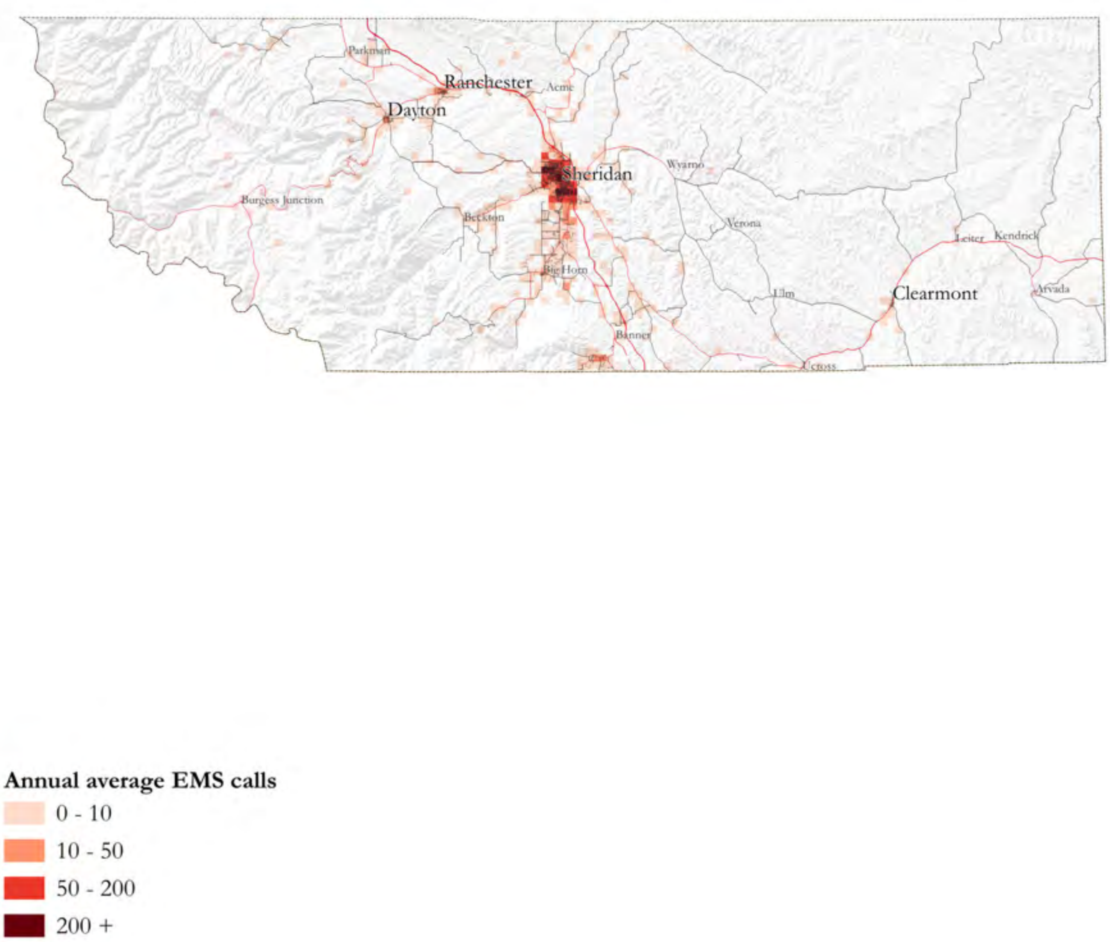
6.2.15 Park County



6.2.16 Platte County



6.2.17 Sheridan County



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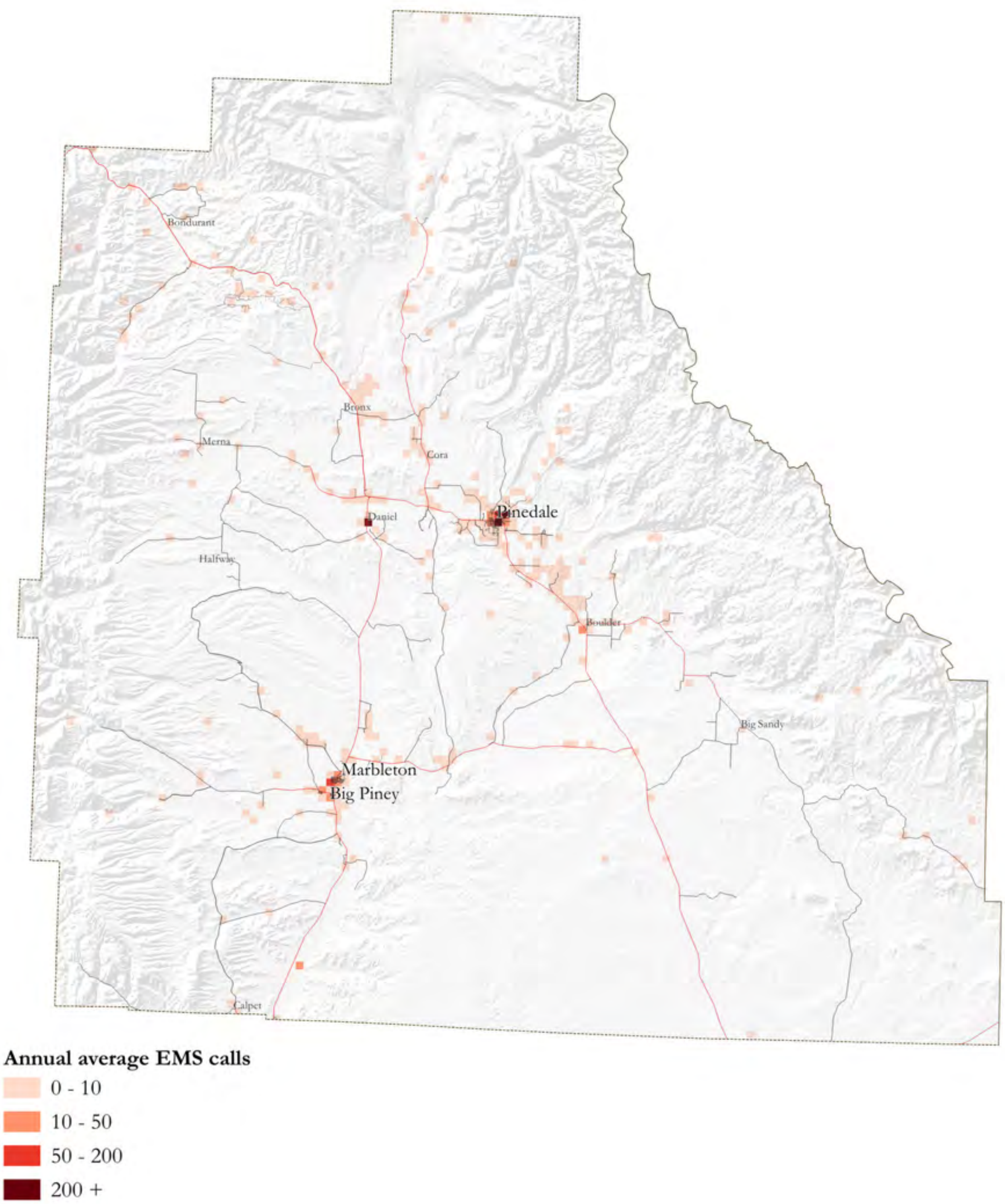

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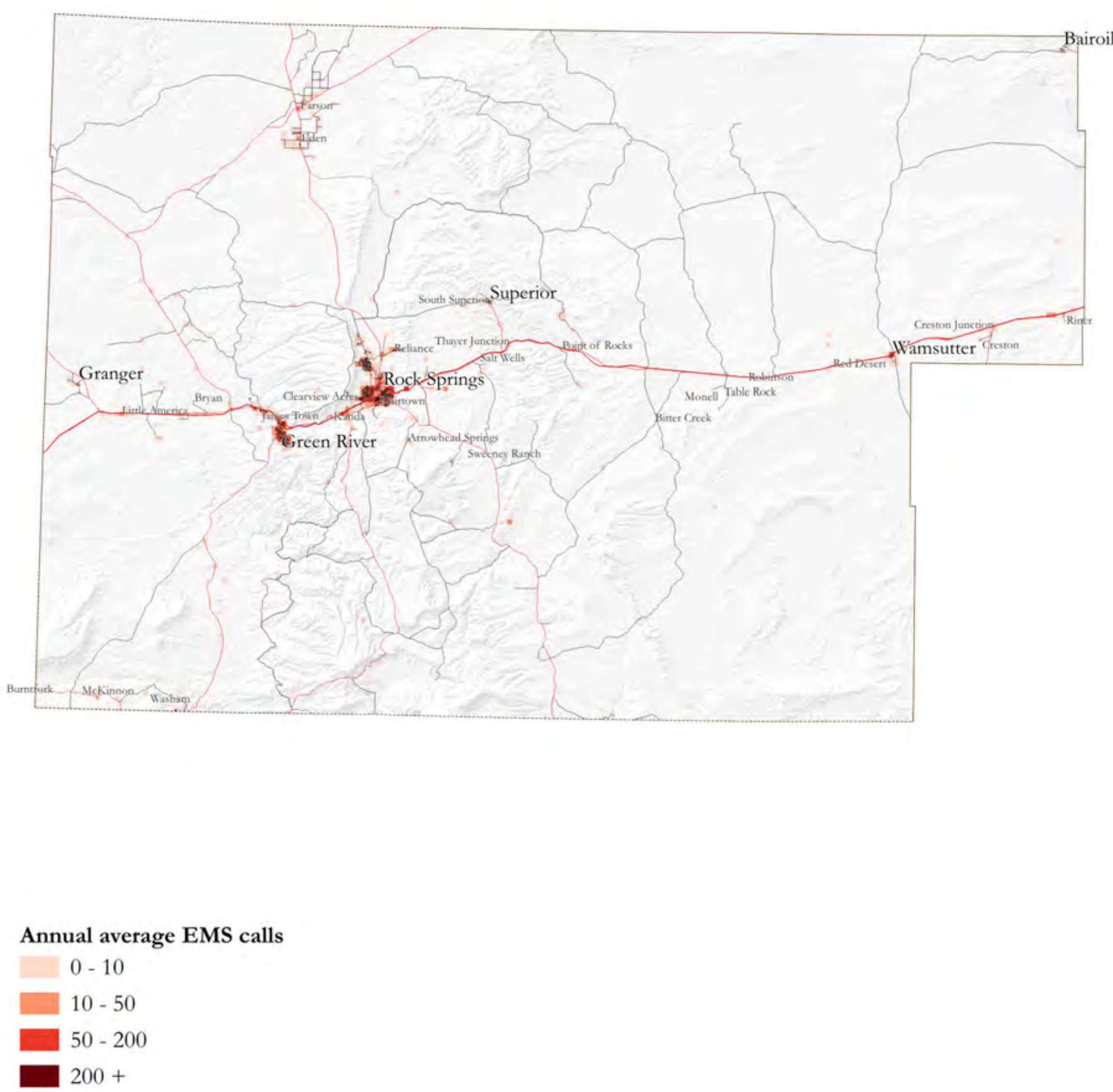

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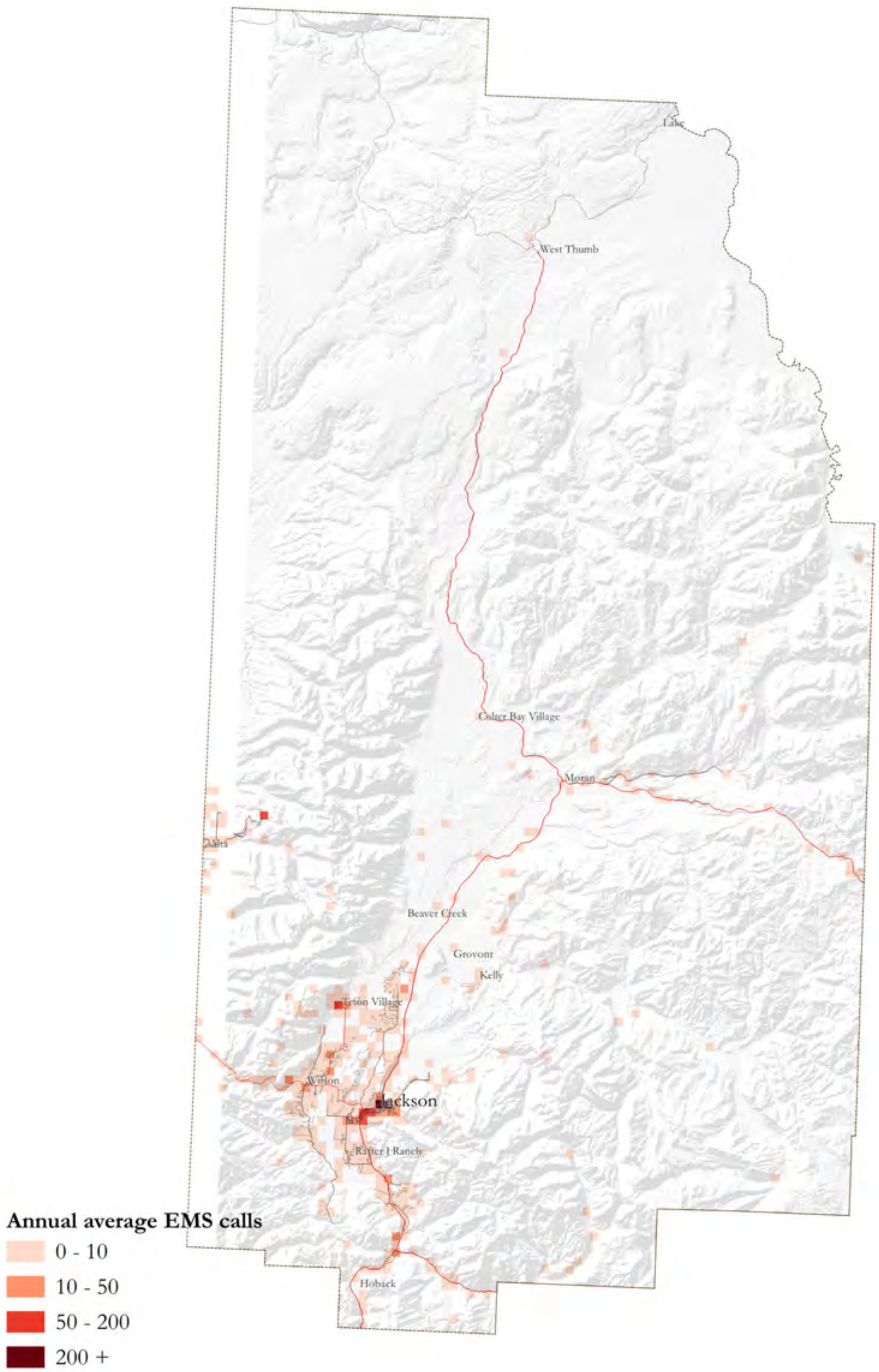

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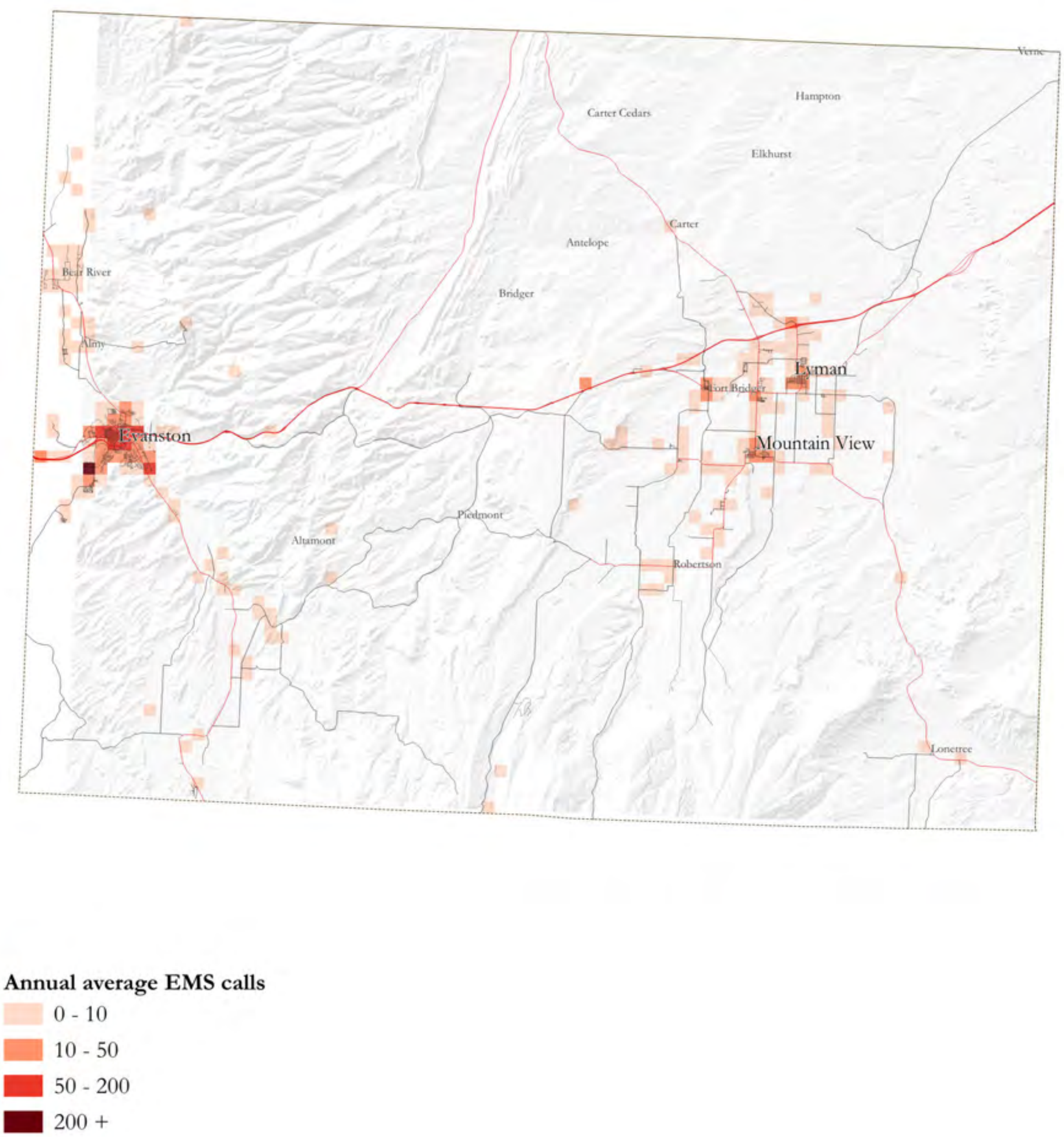

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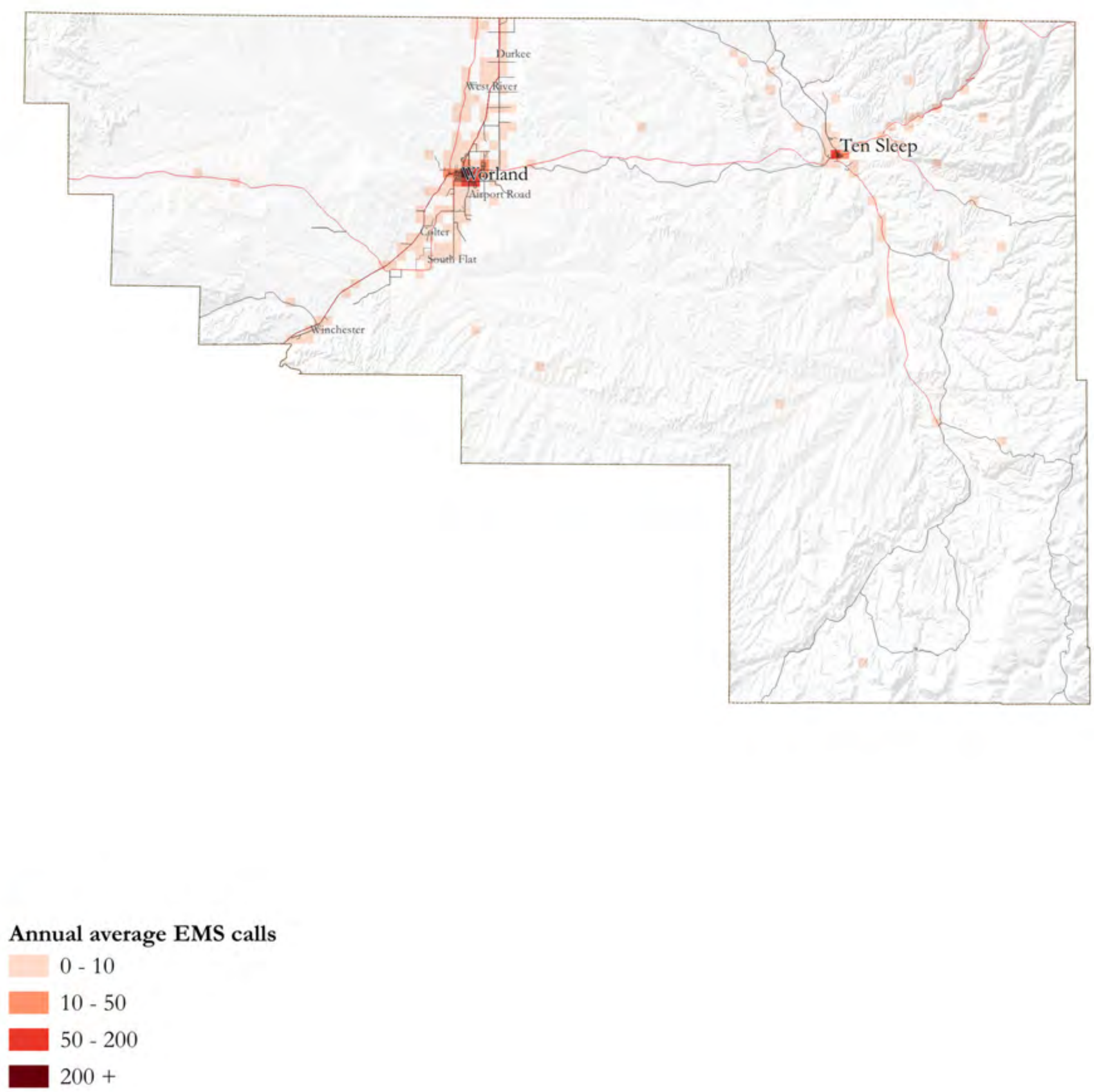

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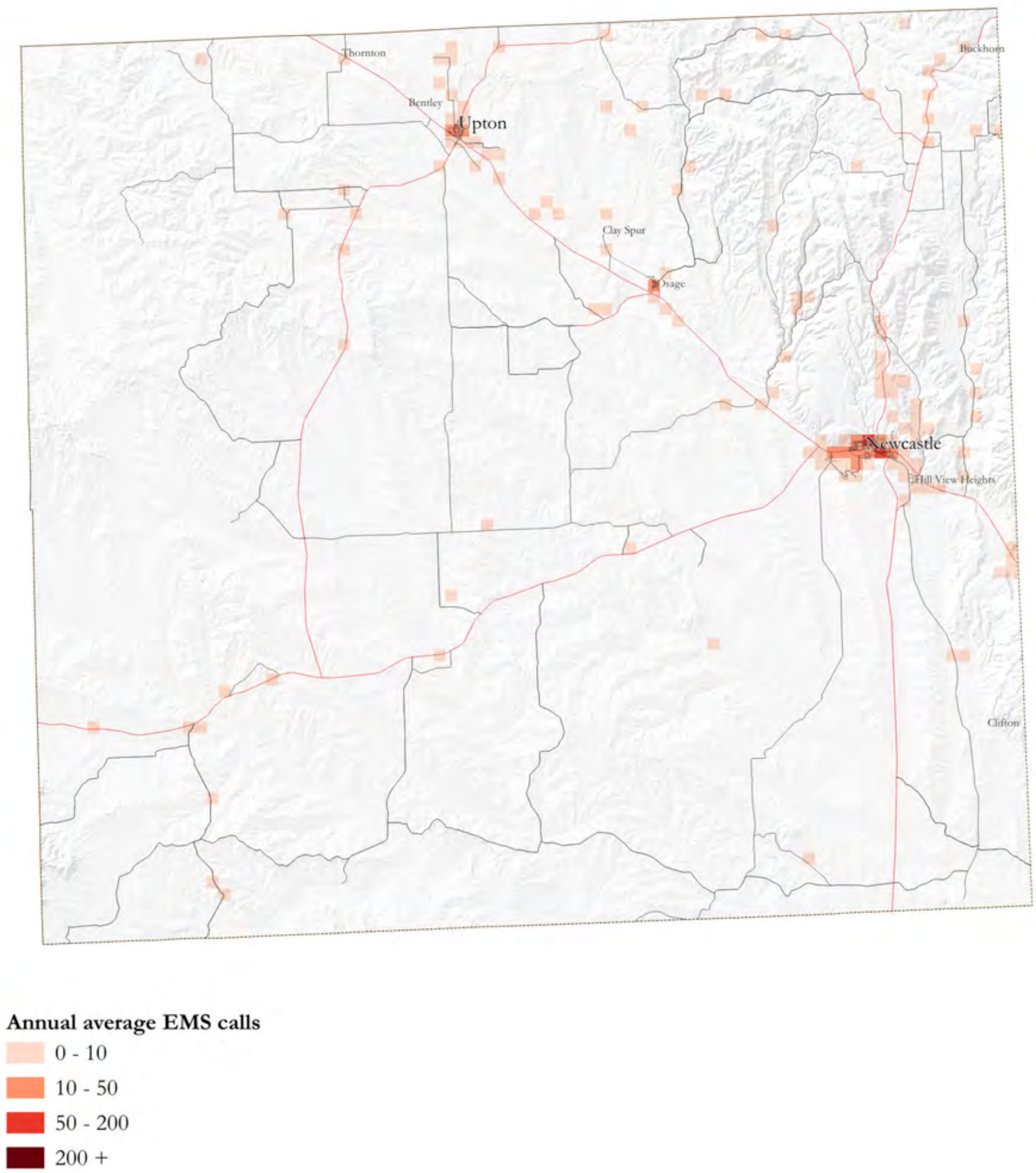


6.3 Highway risk

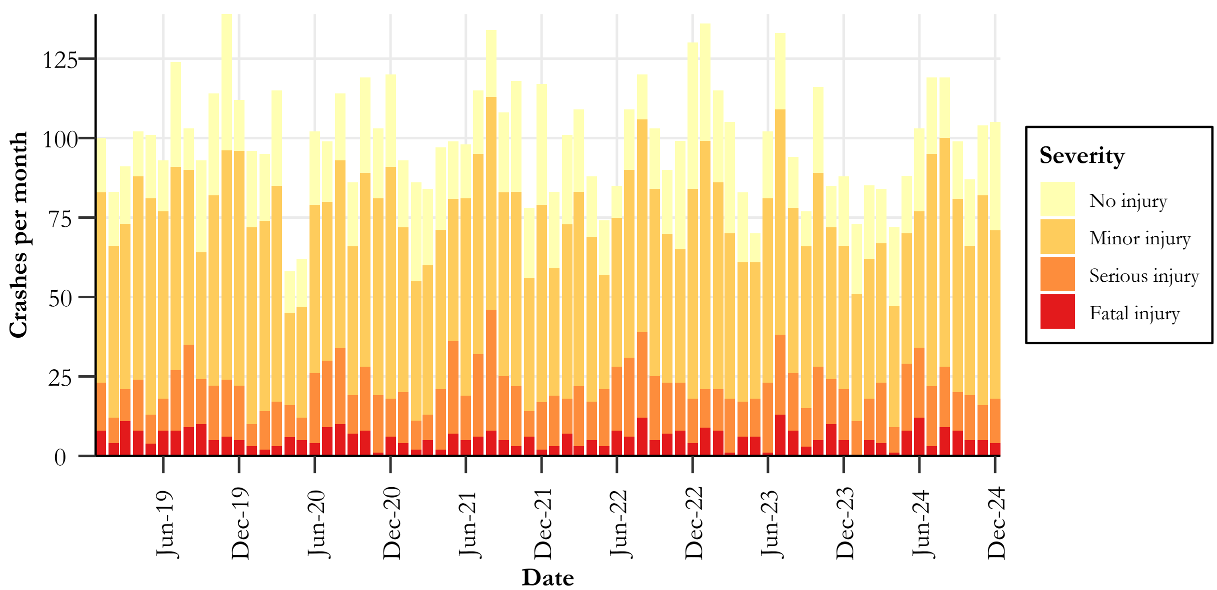
The vast majority of ground EMS calls are local, but an important fraction (between 1-2% of the total, or ~ 1,200) are responses to highway crashes, often to folks who are traveling through the State.

This section provides an overview of these on a Statewide level, using data provided by the Wyoming Department of Transportation on crashes and traffic volume.

Importantly, these data do not distinguish between ground and air EMS responses, so we cannot tease out the ground EMS component by itself.

With that caveat, we begin with Figure 4, which shows the number of crashes over time since 2019, categorized by severity. Aside from a temporary drop during the beginning of the COVID pandemic, and seasonal increases during the summer months, crash volume has remained relatively stable, with 50 to 100 injury-causing crashes occurring each month.

Figure 4: Highway accident volume by severity over time



On the subsequent pages, Figure 5 shows how the volume of EMS calls and EMS response time vary by highway. Figure 6 shows a similar plot, but coloring highway segments based on accident **risk** that is adjusted for estimated traffic volume (per 10,000 annual vehicle miles).

Figure 5: Highway accident volume and EMS response time by milemarker

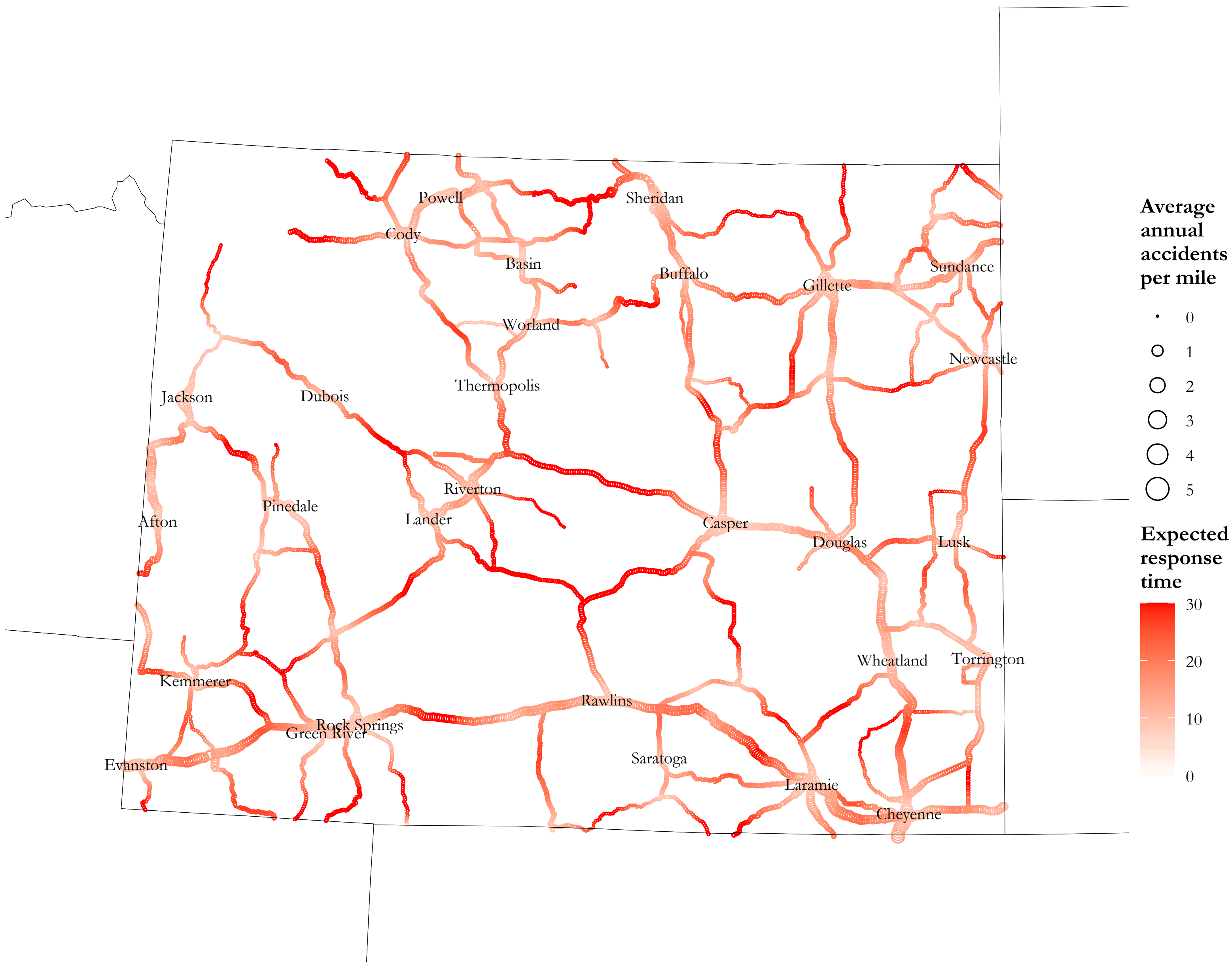
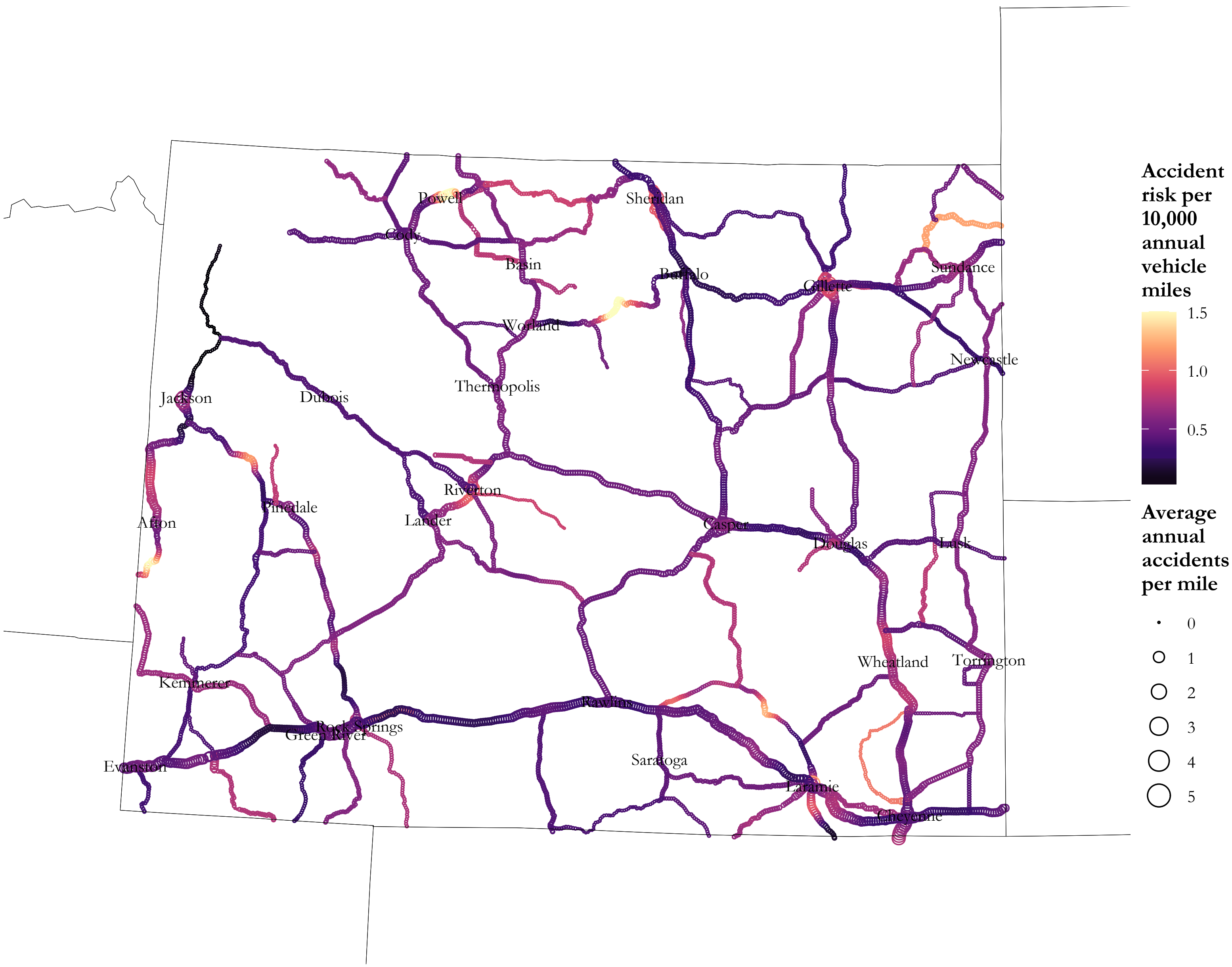


Figure 6: Average crash severity and severity-scaled volume by milemarker



6.3.1 Crash volume and risk for selected routes

The maps on the previous pages show a good geographic overview, but plotting selected routes on a graph gives us a more precise way to compare volume and risk.

On the next pages, Figure 7 shows crash volume by route for 10 major highways. Each little panel has milemarkers on the x-axis and the 10-year average number of crashes per mile on the y-axis. The small gray circles show the raw average counts, and the red lines and shaded region show the smoothed trend. We also overlay major cities along the route to orient readers who may not be familiar with specific milemarkers.

Figure 8 shows the same routes, but this time, the crash *risk* —i.e., dividing the number of crashes by the average number of vehicles passing through that milemarker.

We note some stylized facts from these maps and charts, none of which should be surprising to the average Wyomingite:

- Crash volume tends to be highest around major cities, likely due to local business traffic entering and exiting highways. Figure 7 shows this clearly, e.g., around Casper, Cheyenne, Rock Springs, Gillette, Jackson, etc.
- Risk (adjusted for traffic), however, tends to be higher in the mountains or more remote stretches exposed to poor weather. Note the passes over the Big Horns on Figure 6, the elevated risk on I-25 between Chugwater and Glendo, and the usual suspects on the "Snow Chi Minh Trail" evident on Figure 8. By contrast, risk is relatively constant over the US-85 corridor.
- EMS response times are understandably much faster around cities, particularly compared to remote stretches like Muddy Gap to Sweetwater Station, Casper to Shoshoni, and Bill to Wright.

Figure 7: Injury-causing crash volume for selected highways

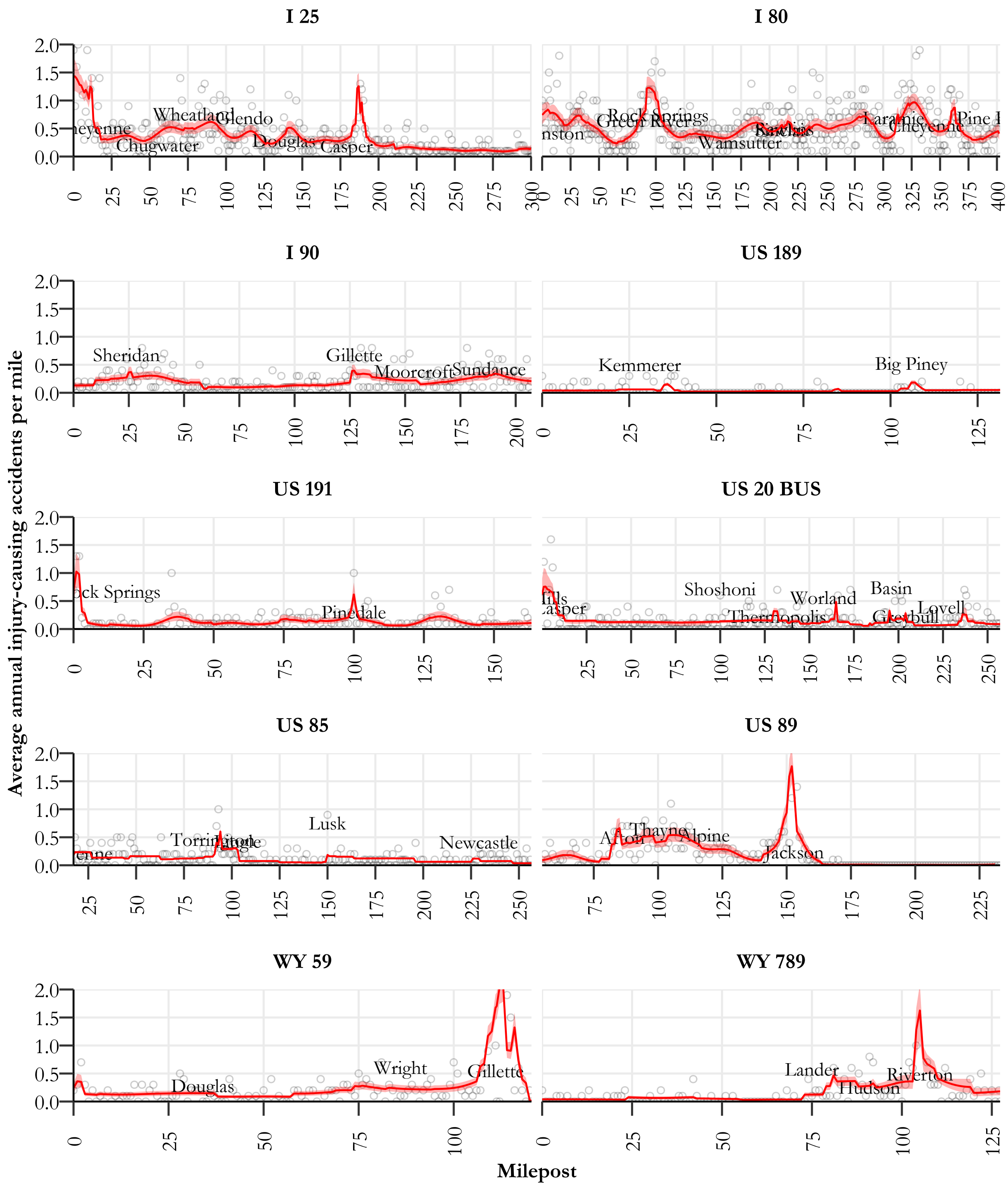
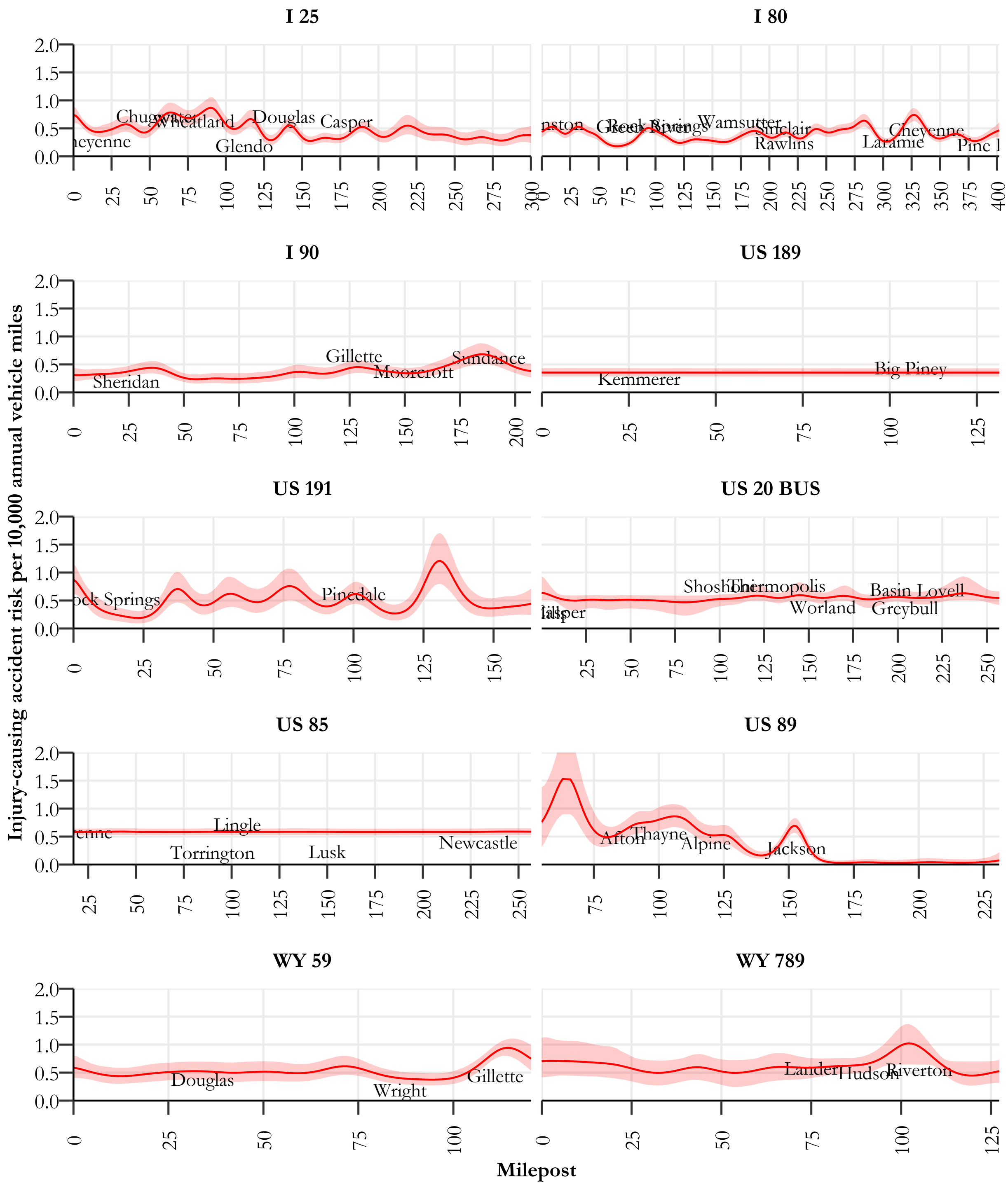


Figure 8: Injury-causing crash risk for selected highways



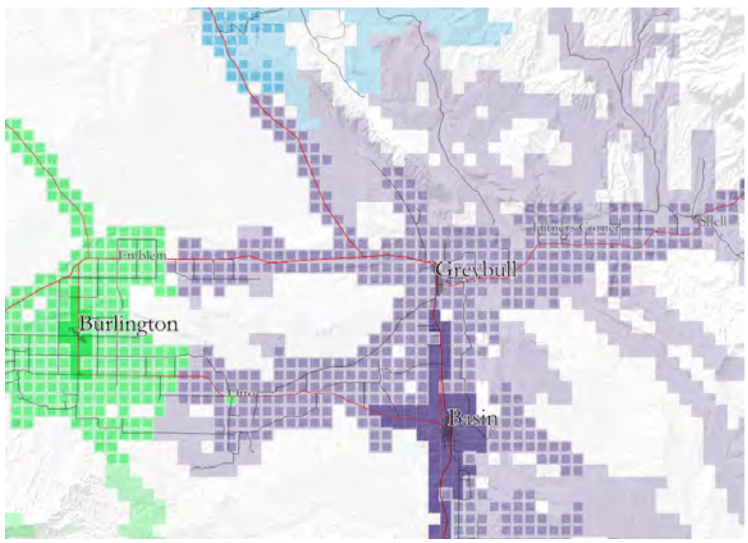
7 EMS coverage estimates

Pivoting away from volume and risk, we now look at coverage; that is, for a call coming from any given corner of Wyoming, which EMS services is most likely to respond, what what is the expected response time?

7.1 Geographic service areas and response times

We begin with a series of maps showing both *service areas* (which EMS agencies are likely to respond) and *response times* (given the agency serving each location, what is the average time it takes to arrive at the patient's location?)

Figure 9: EMS service areas around Basin



As with the geographic demand graphics, we use the grid square as the basic unit of measurement. Figure 9 shows an example, again for the Basin area. In this example, we see three services areas:

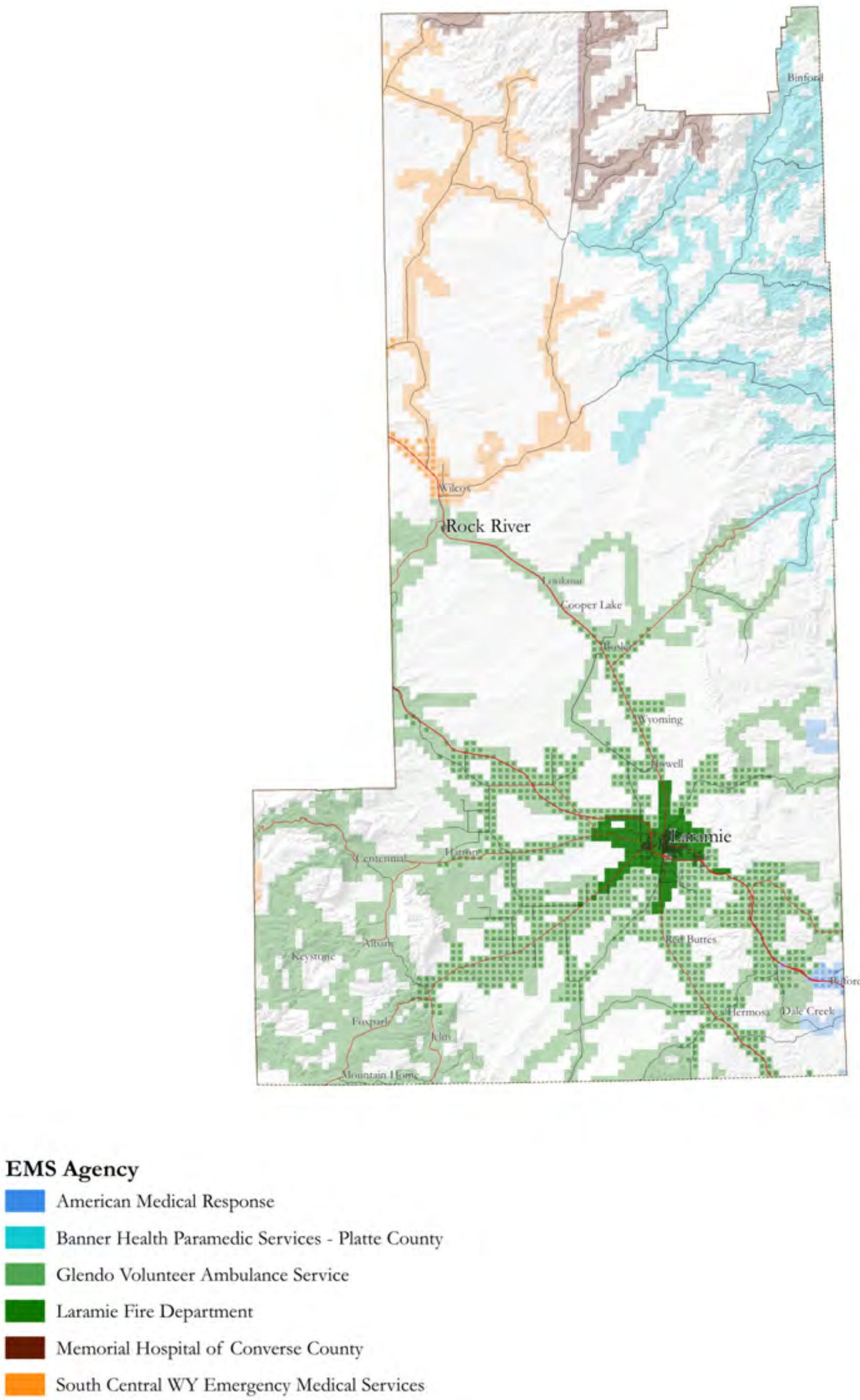
- The **green** is the Burlington Fire Department;
- **Purple** represents the Cody Regional Health ambulance based in Basin; and
- **Light blue** represents the North Big Horn hospital ambulance in Lovell.

In addition to the colors, response times are indicated by the shading:

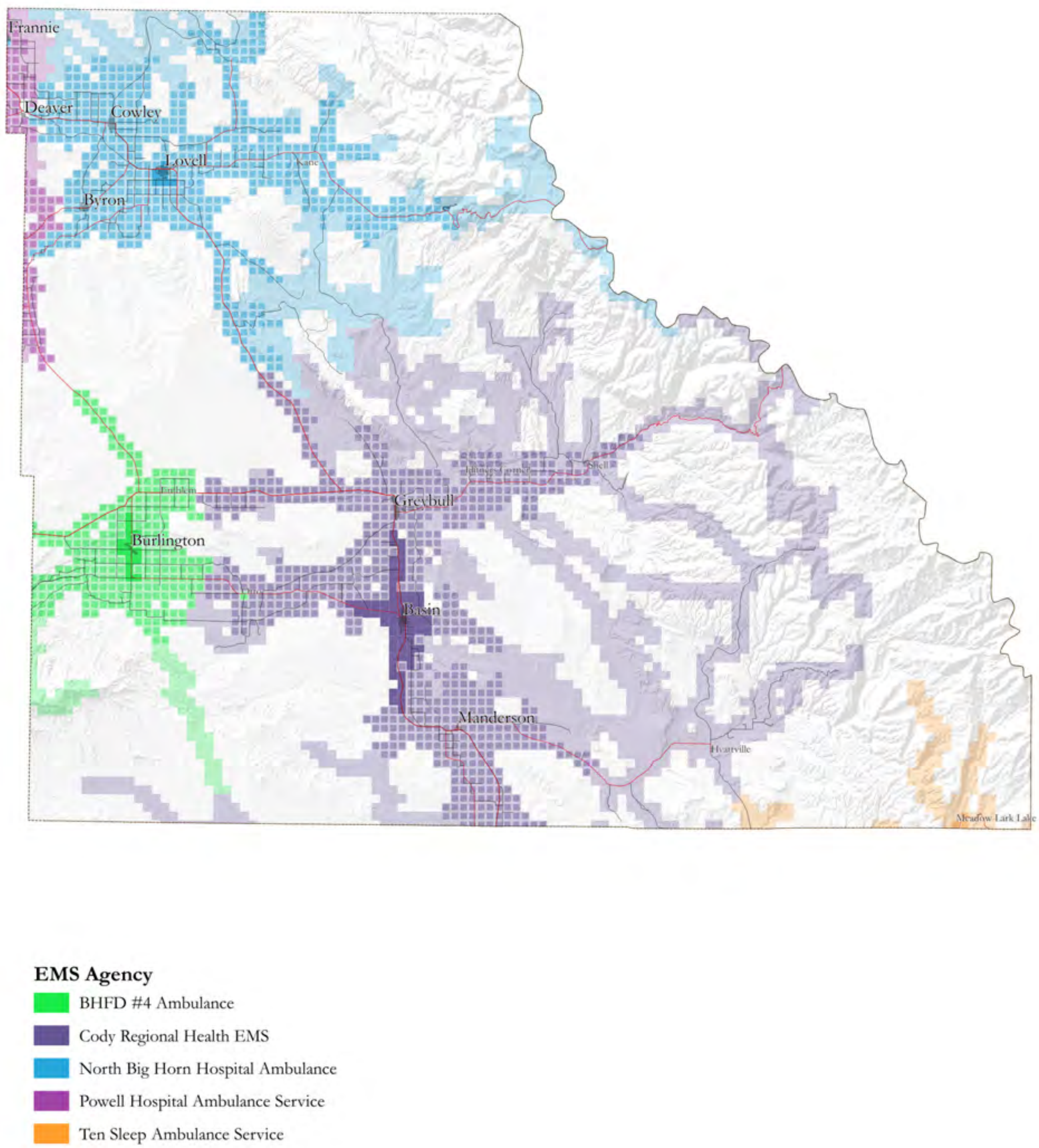
- **Solid, dark colors** show areas with a predicted time of less than 9 minutes;
- The **medium-shaded squares** show areas with expected times between 9 and 30 minutes; and,
- The **light shaded areas** indicate areas where the response time exceeds 30 minutes.

Areas with no shading at all are either inaccessible by ground ambulance (e.g. not near a roadway), or areas where our service area model is uncertain as to which agency would have more than 50% probability of responding.

7.1.1 Albany County

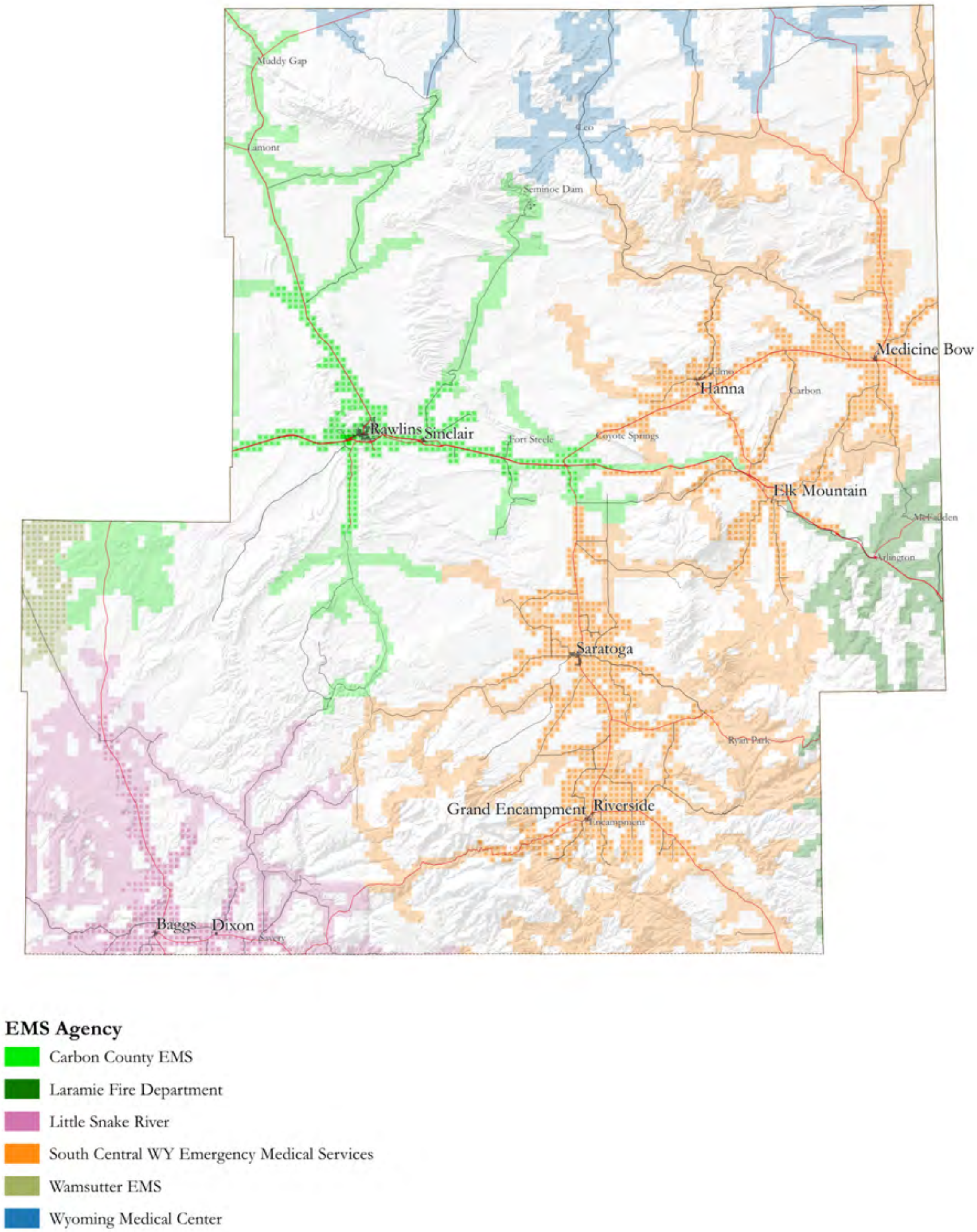


7.1.2 Big Horn County

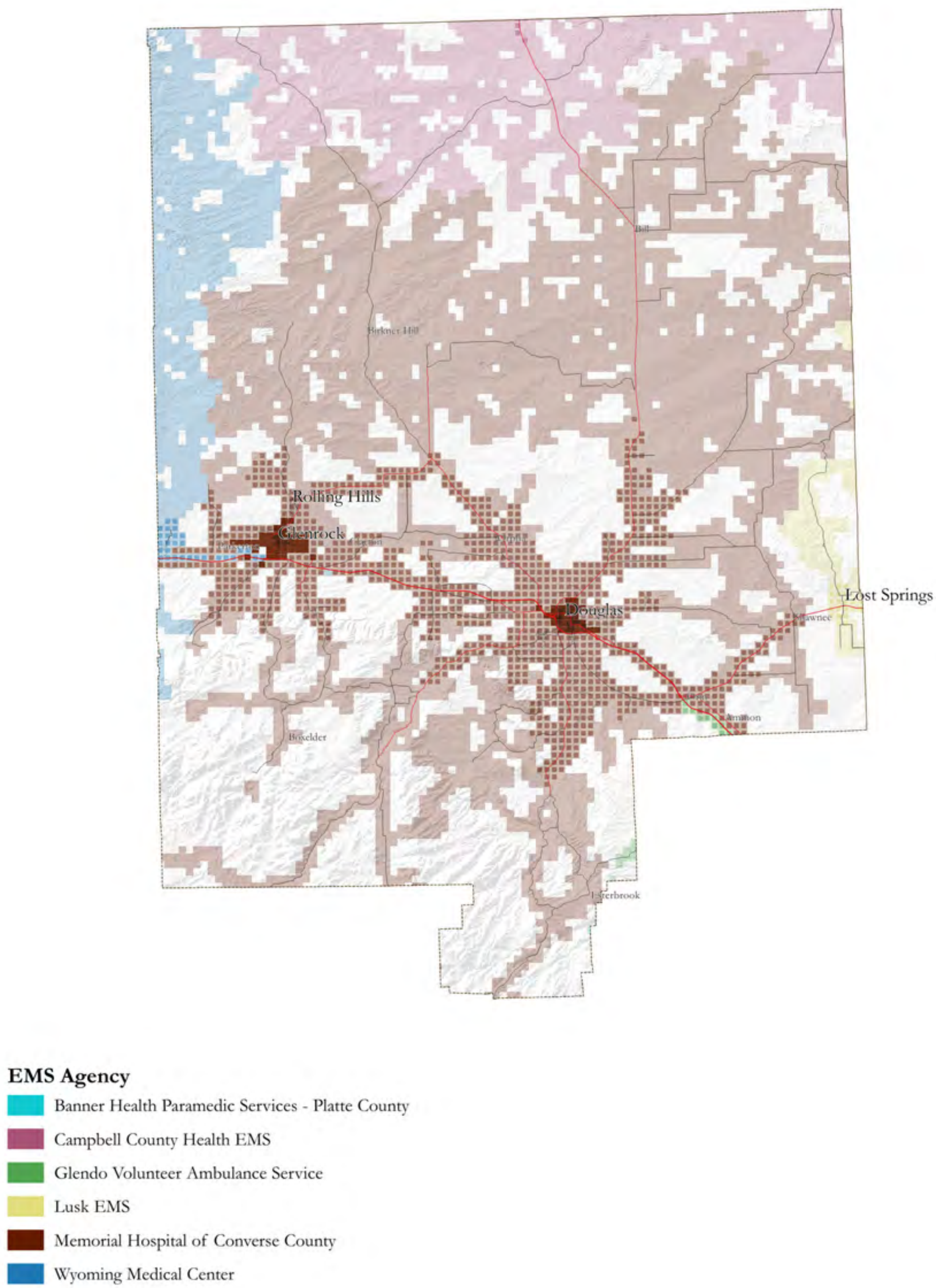


7.1.3 Campbell County

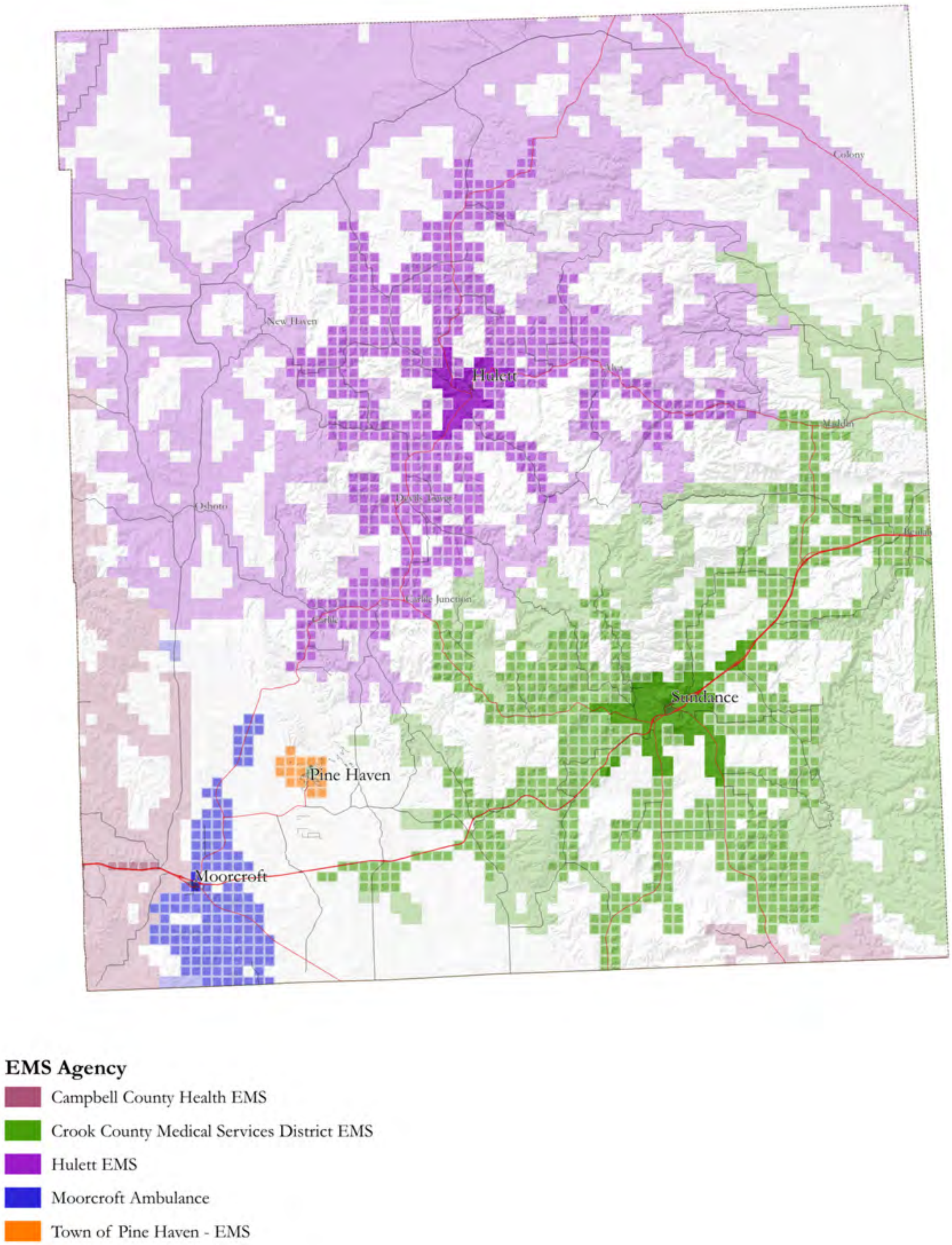
7.1.4 Carbon County



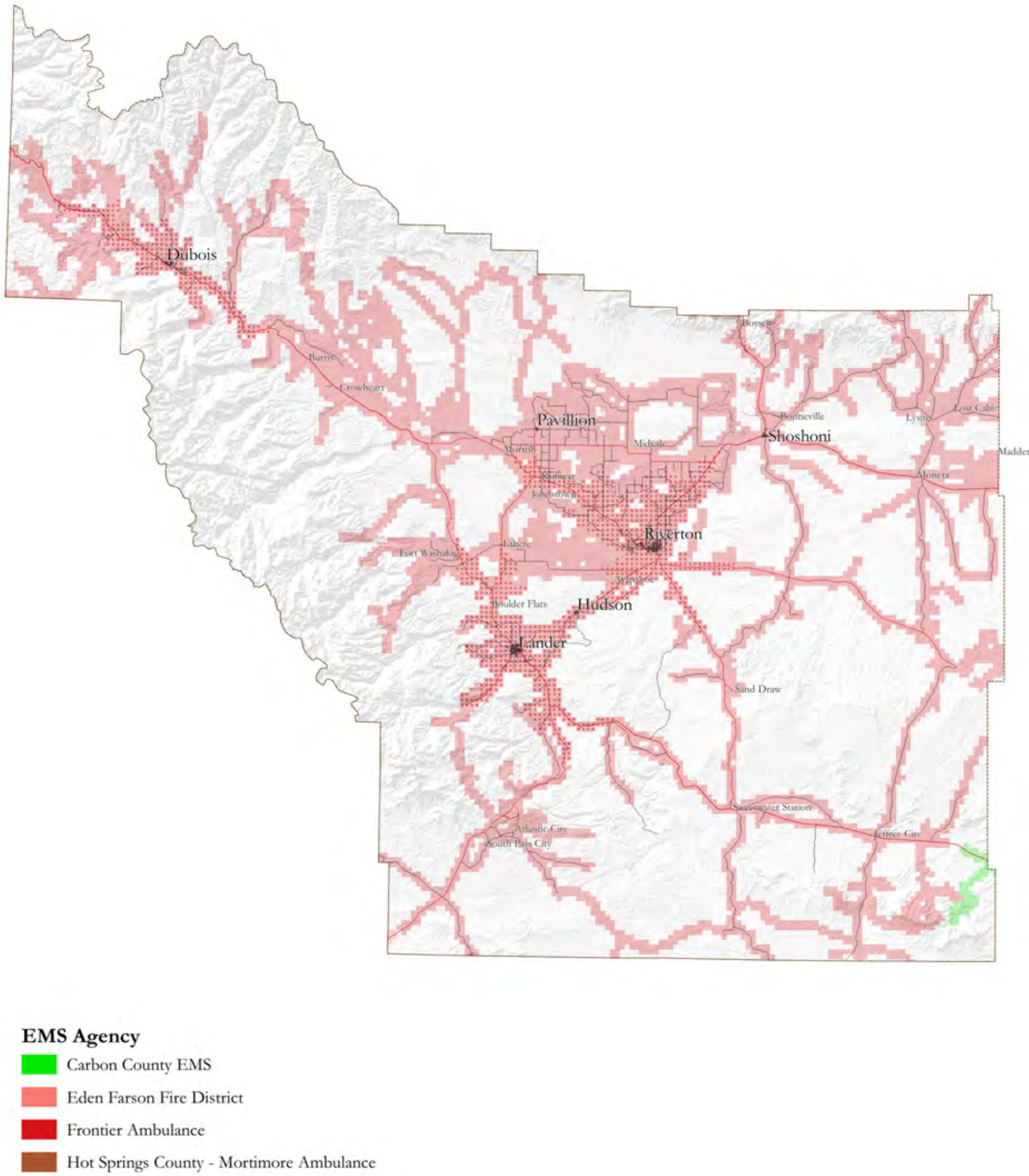
7.1.5 Converse County



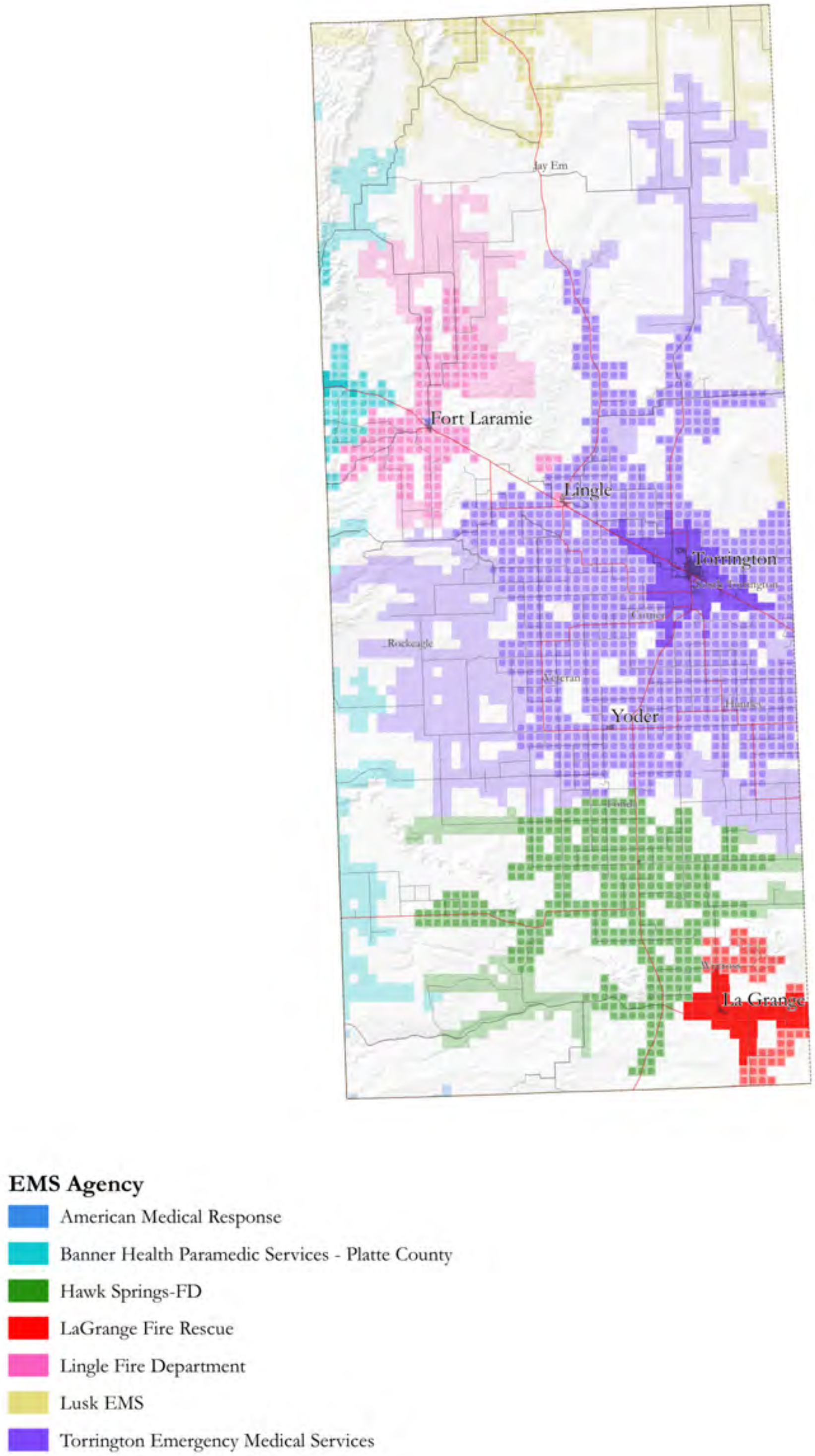
7.1.6 Crook County



7.1.7 Fremont County



7.1.8 Goshen County



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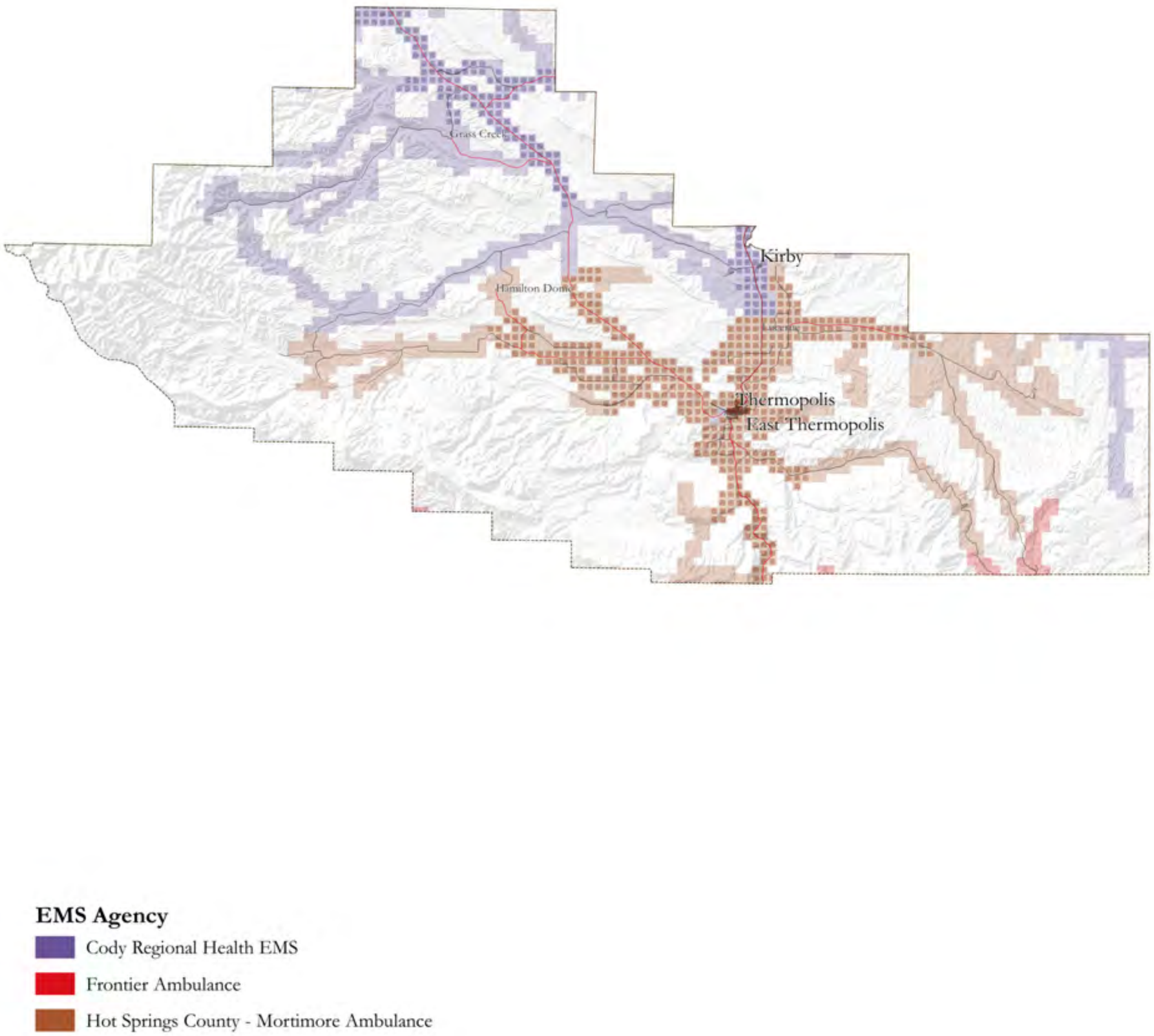

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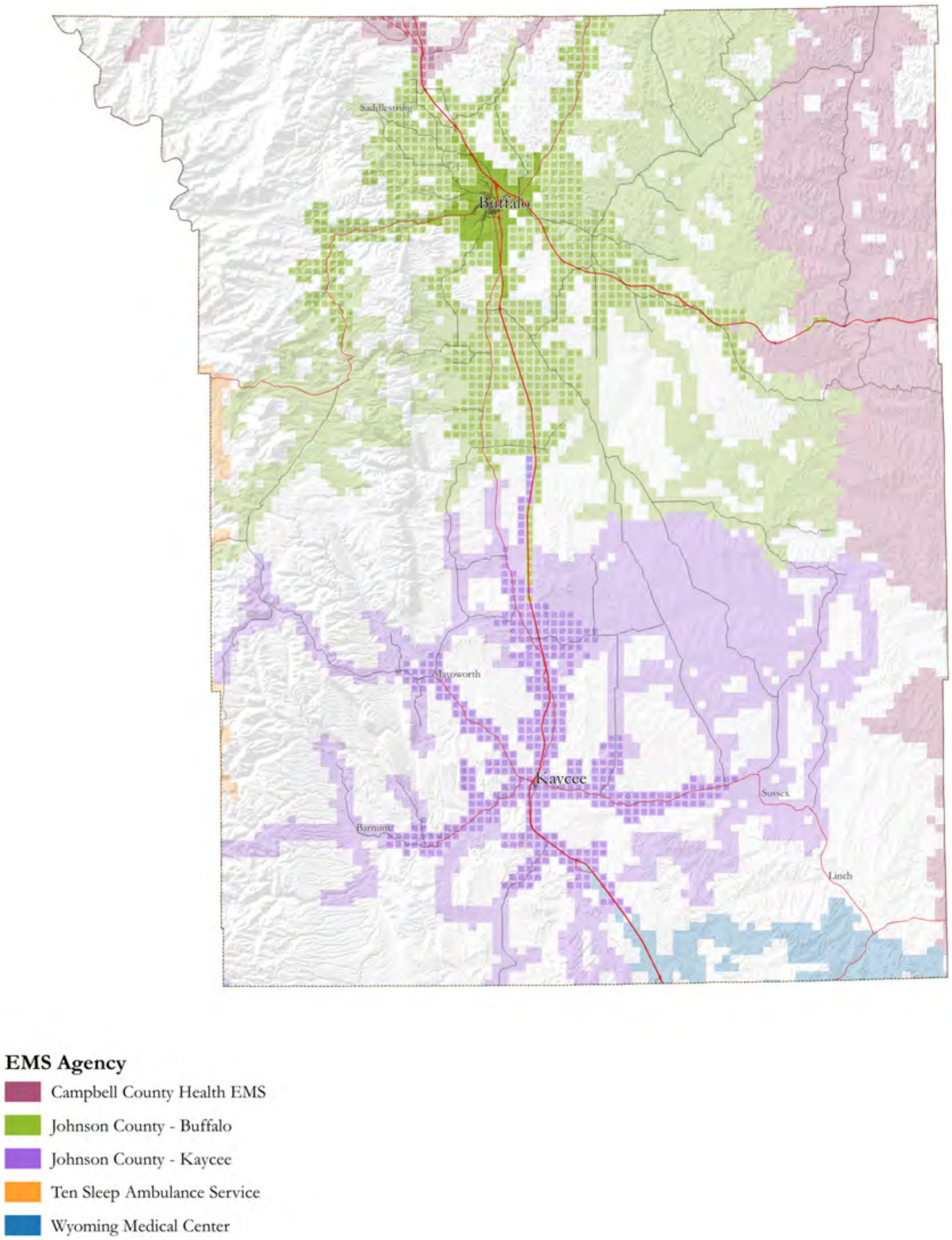
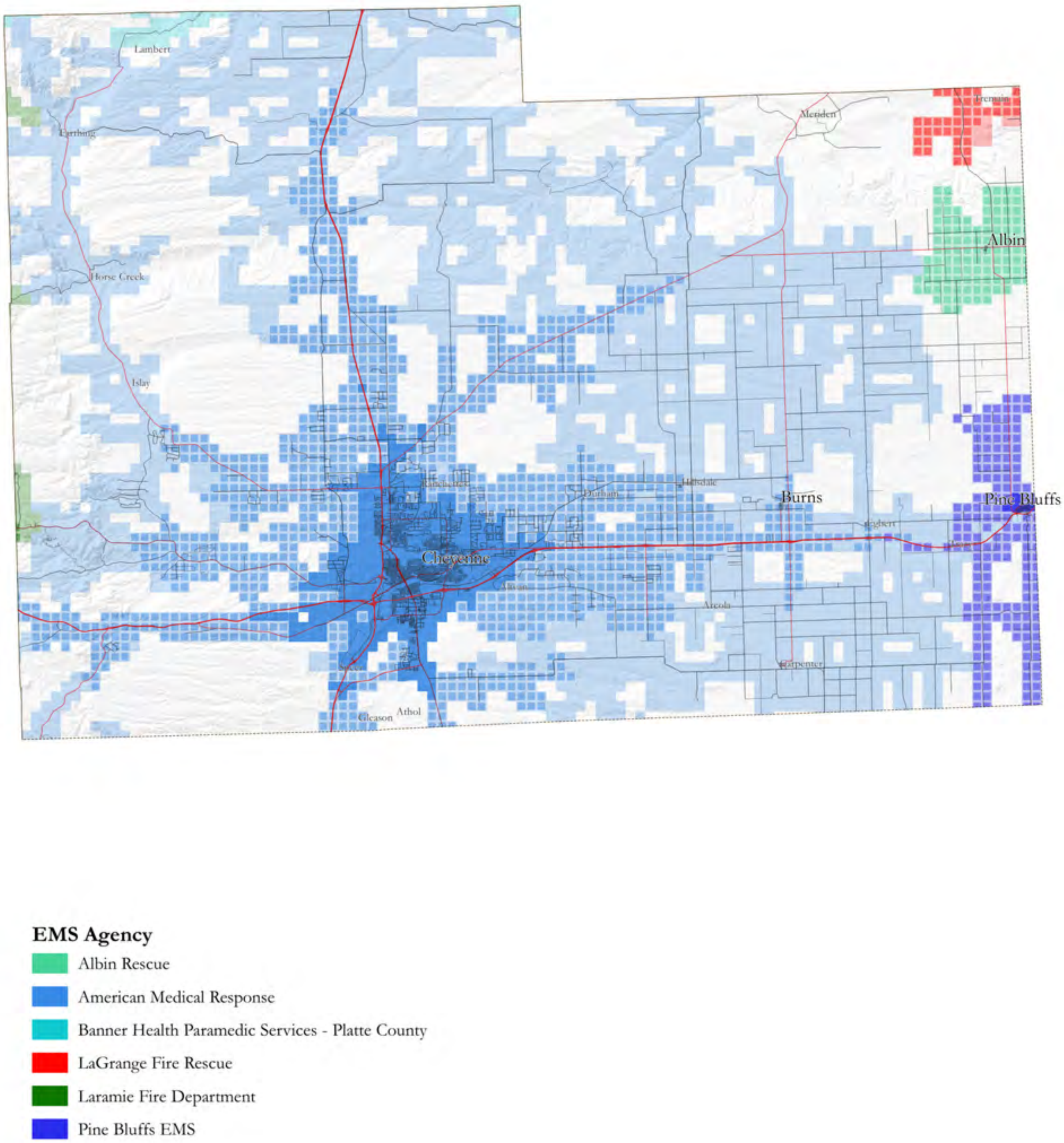


7.1.11 Laramie County



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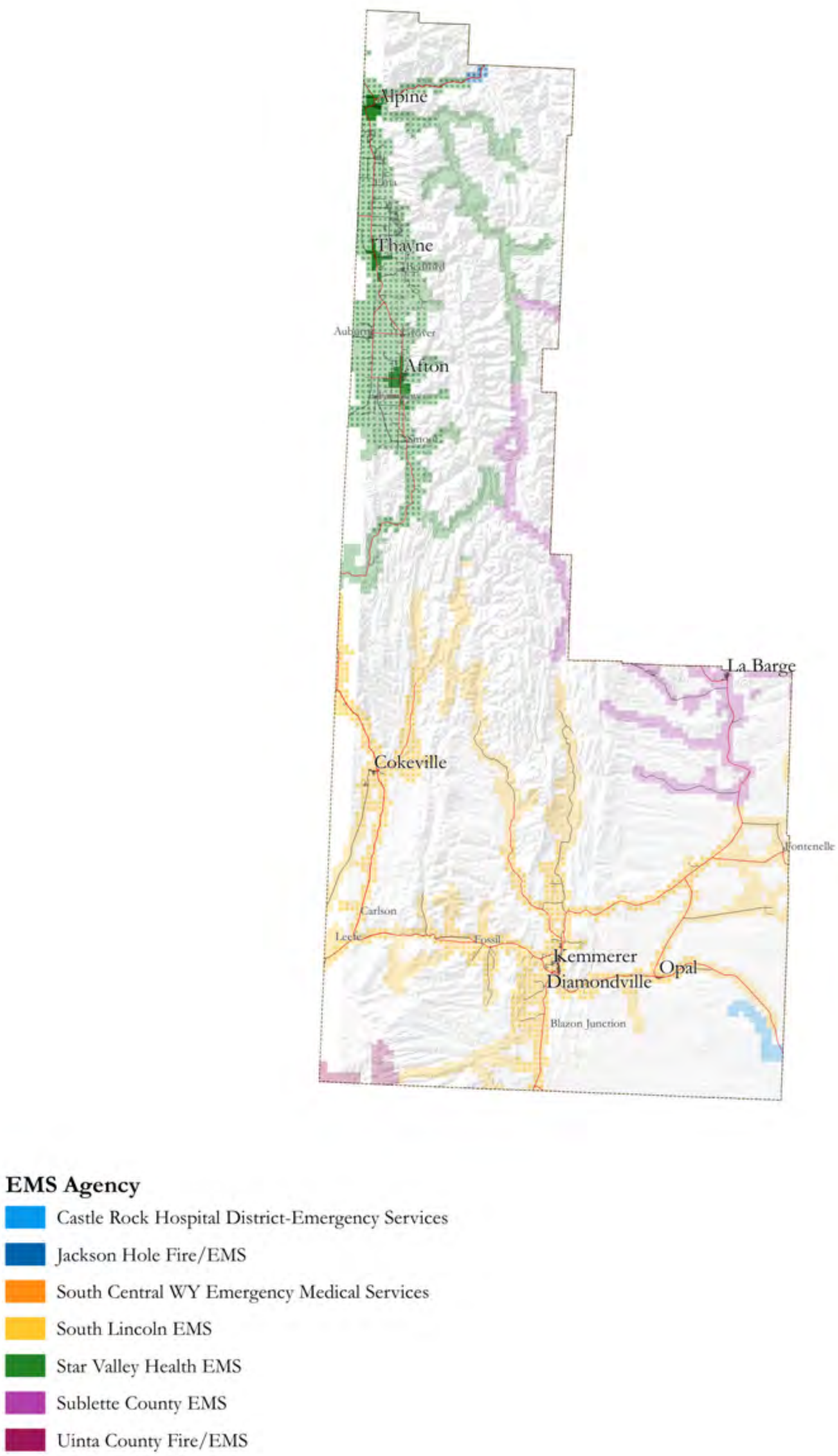

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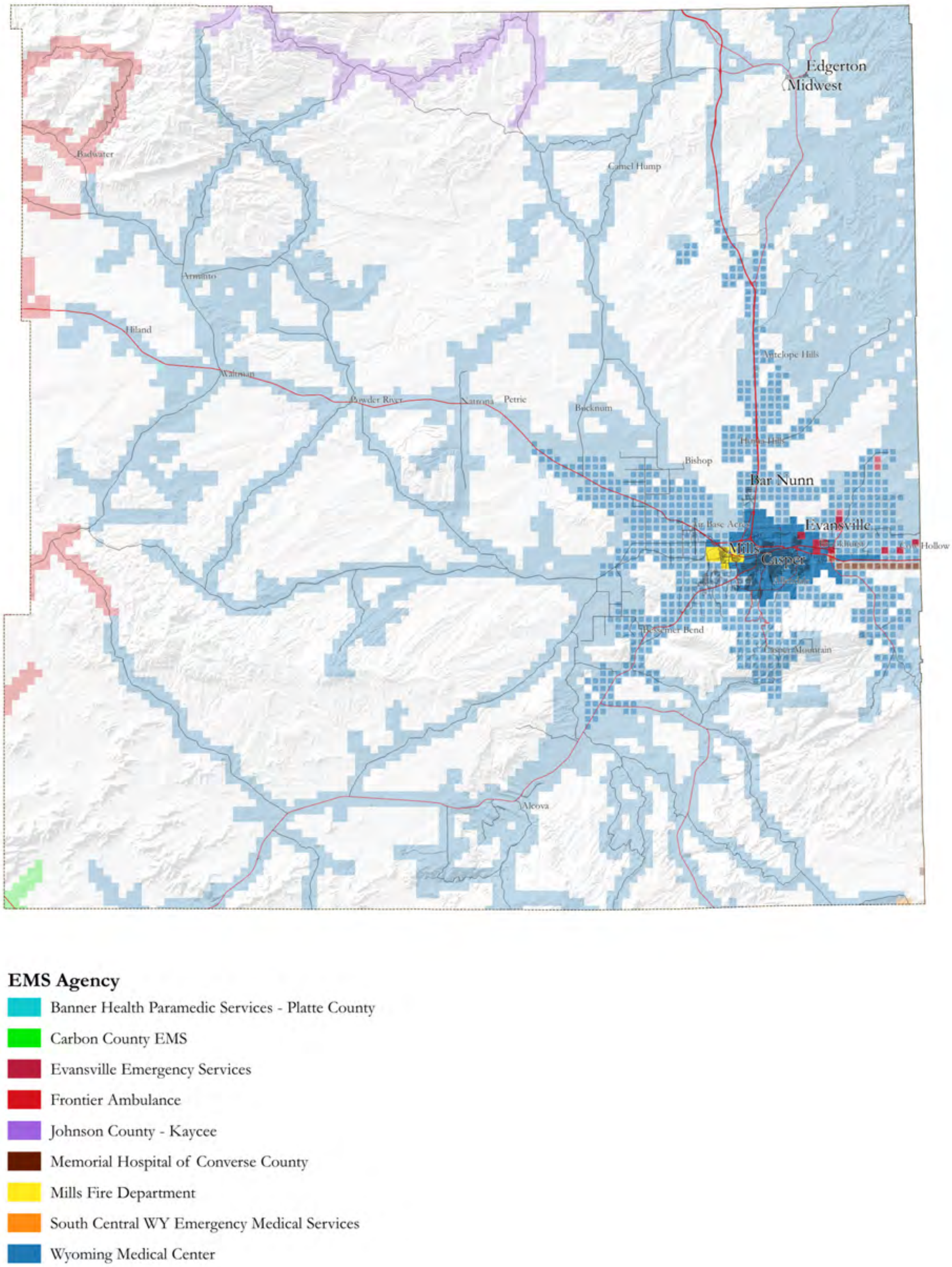

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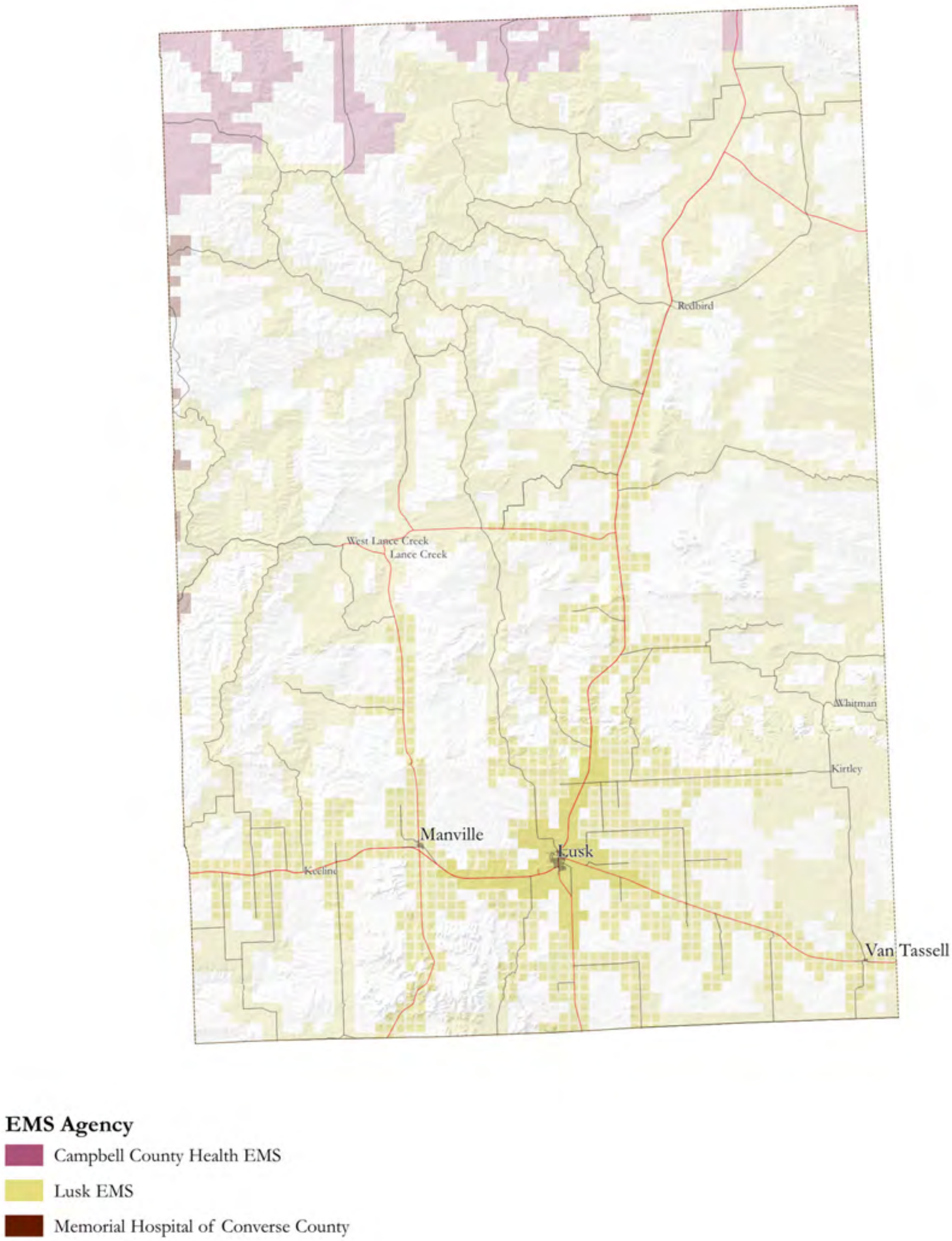
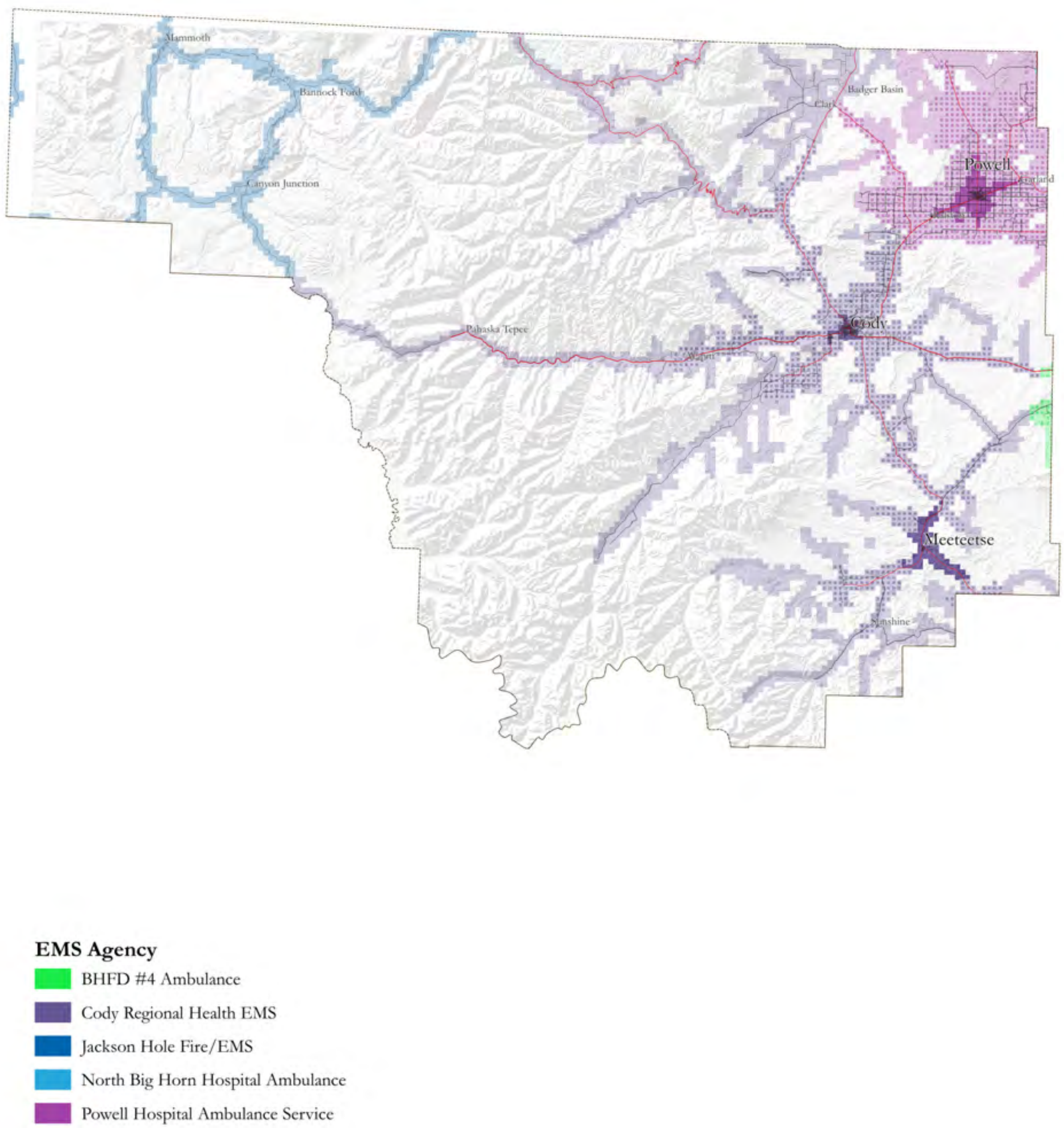
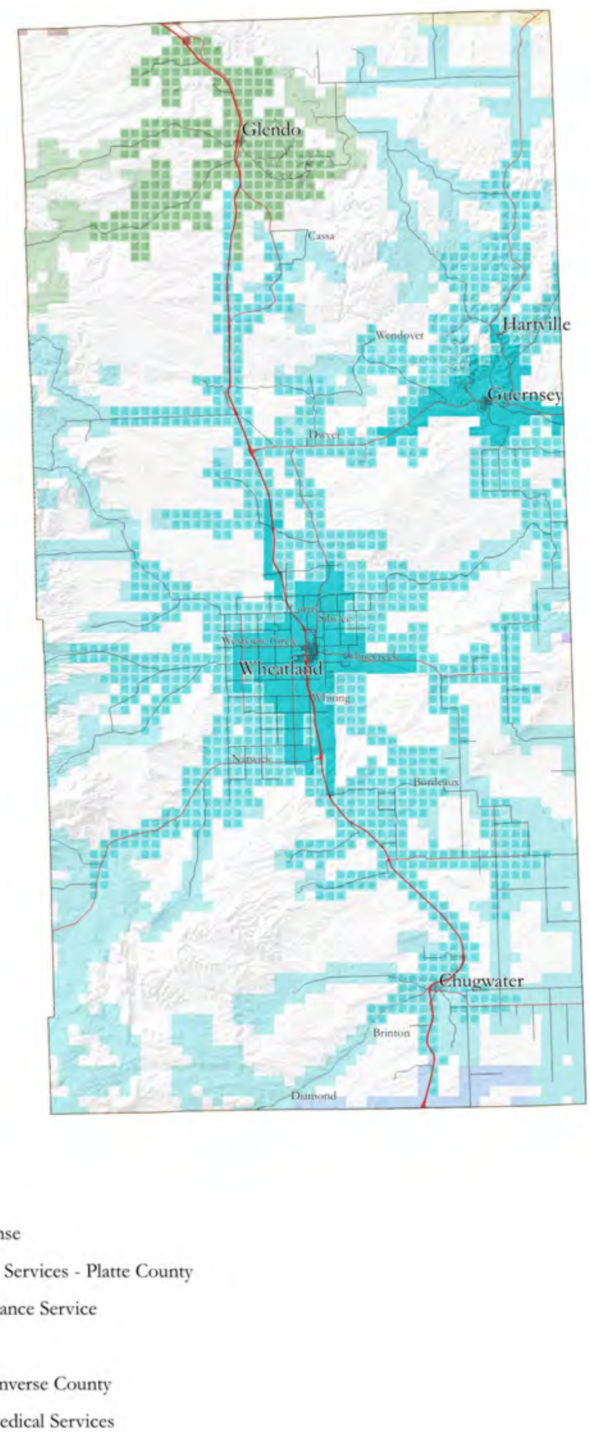


7.1.15 Park County



7.1.16 Platte County



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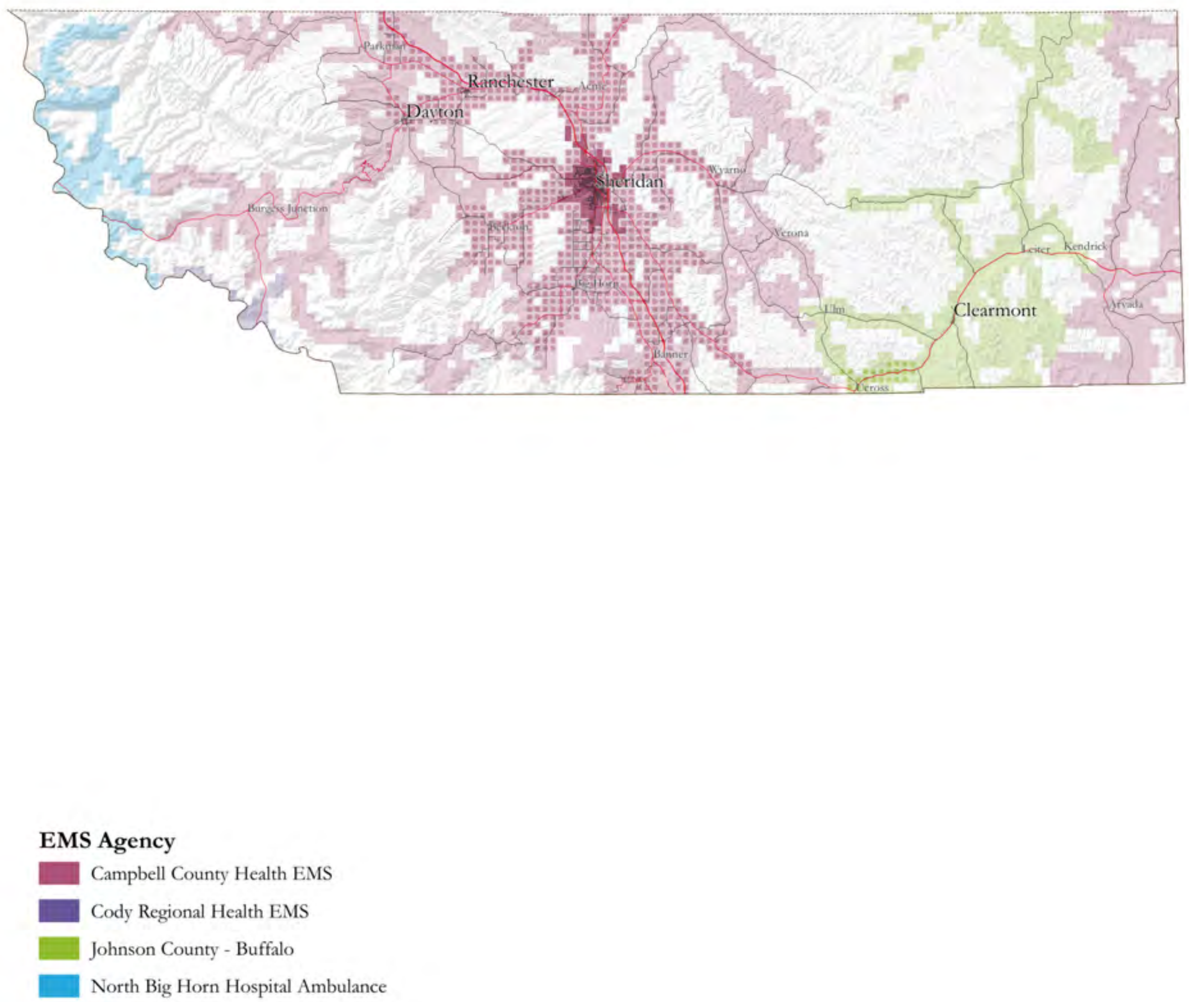

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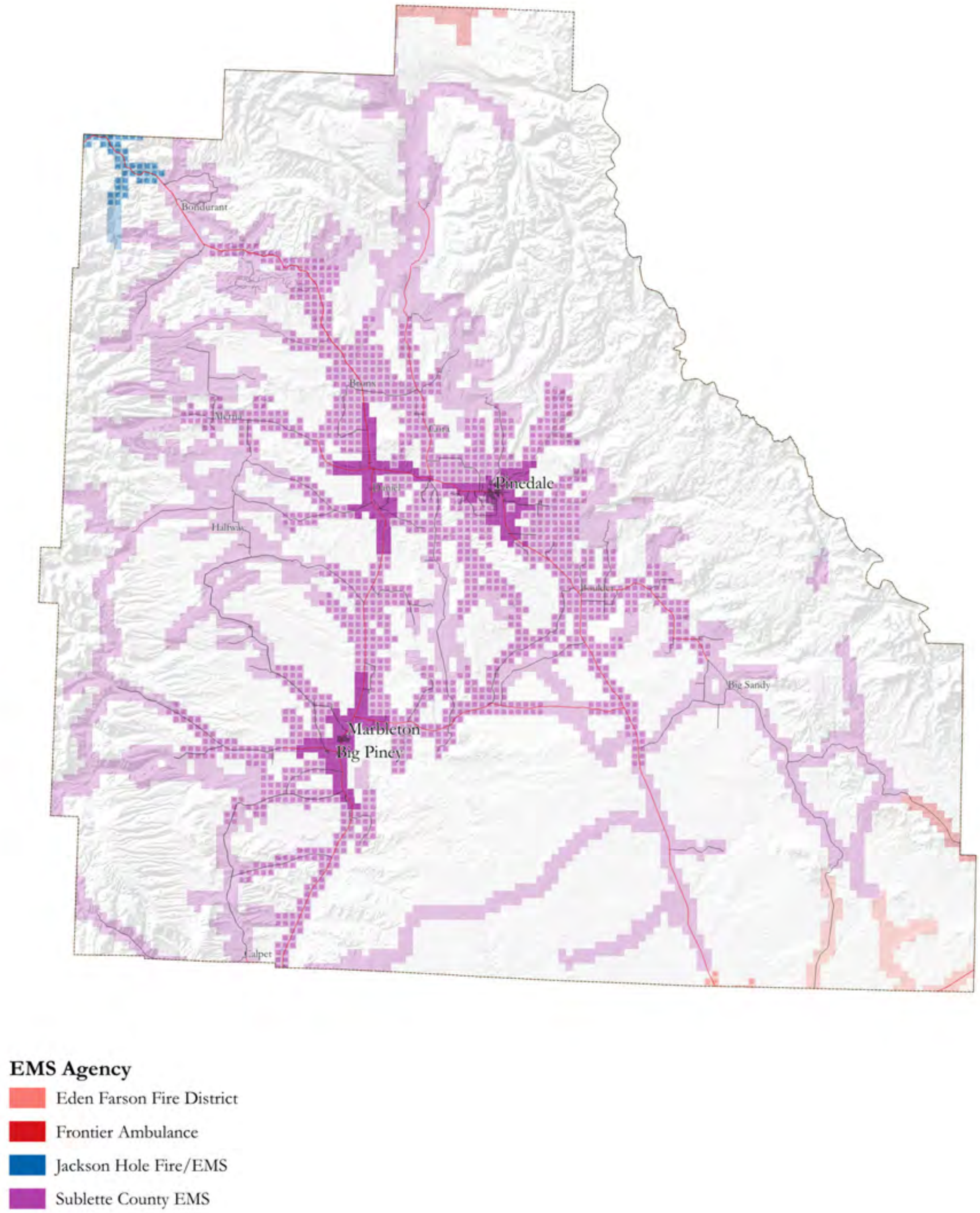
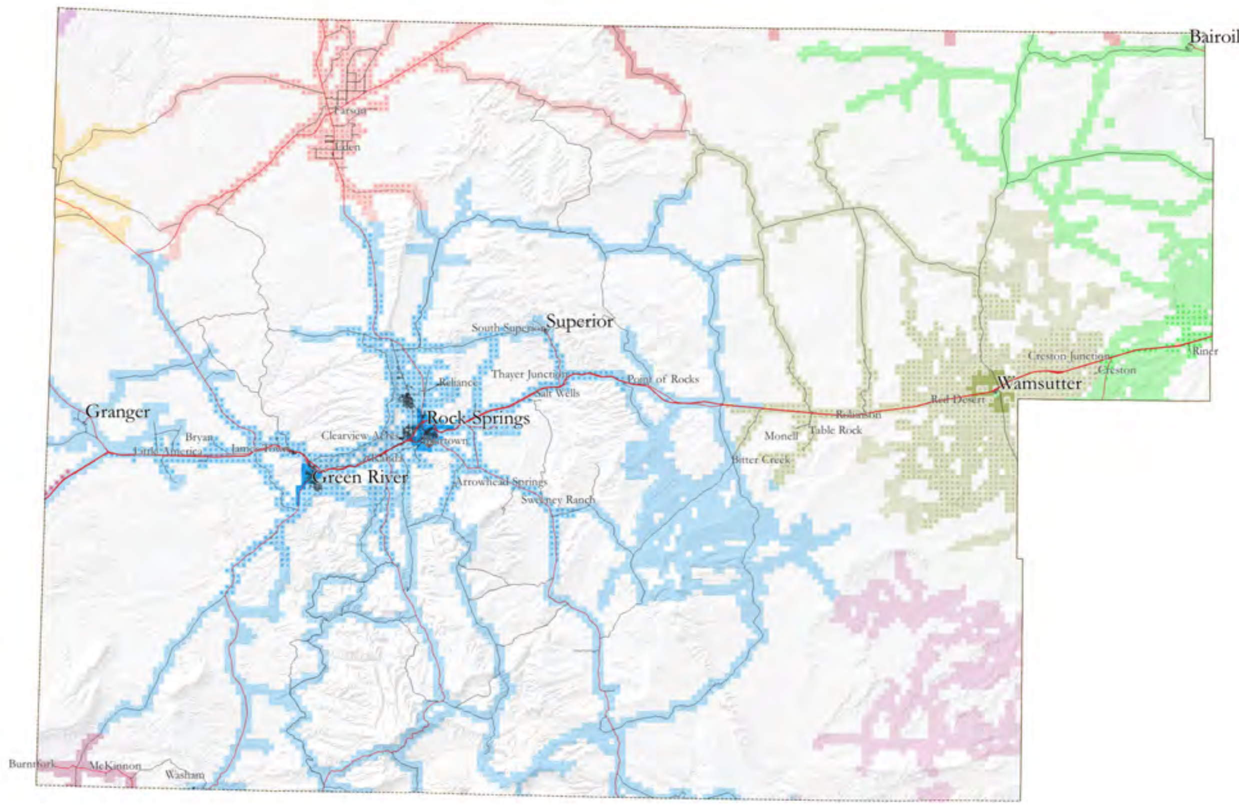


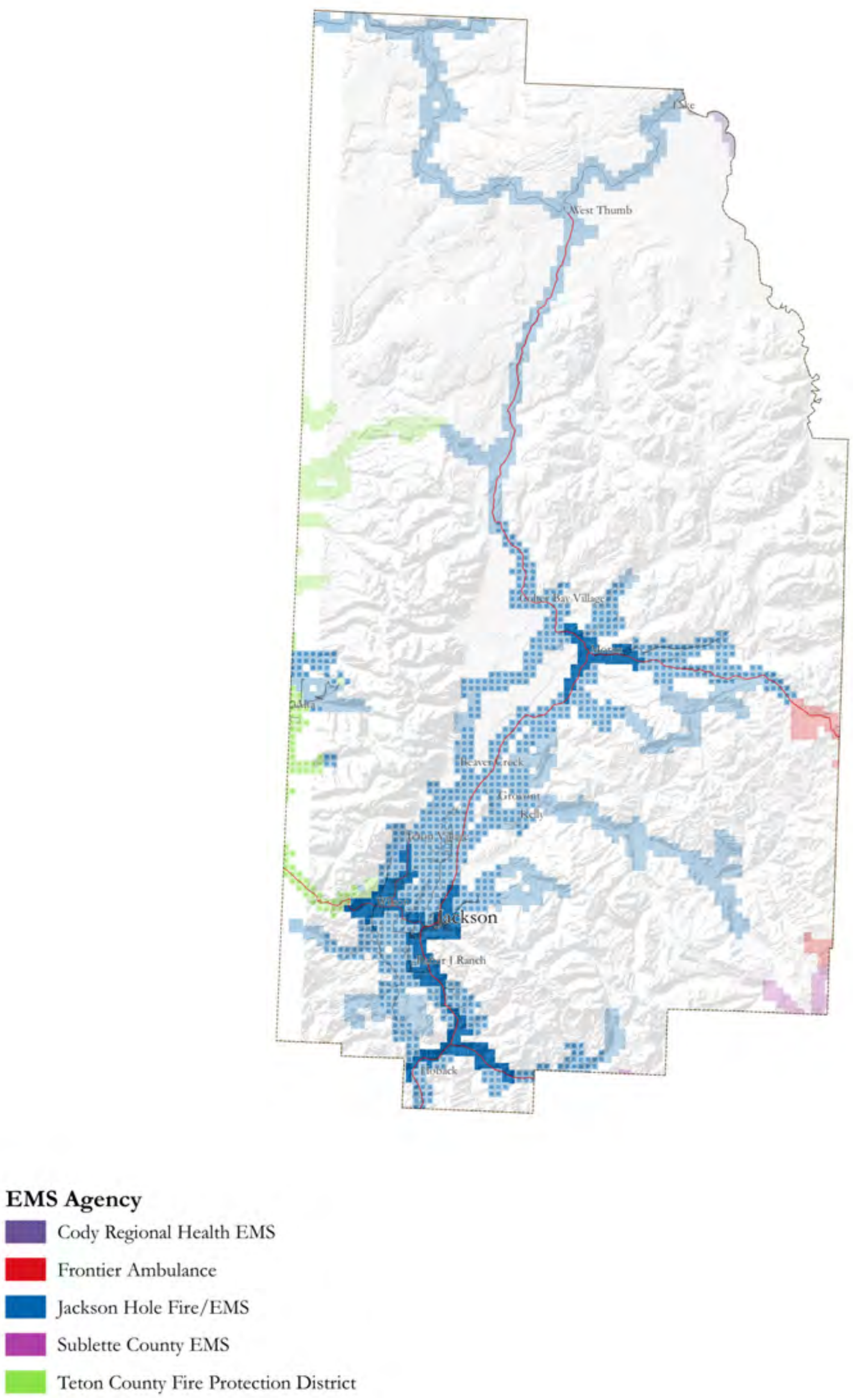
7.1.19 Sweetwater County



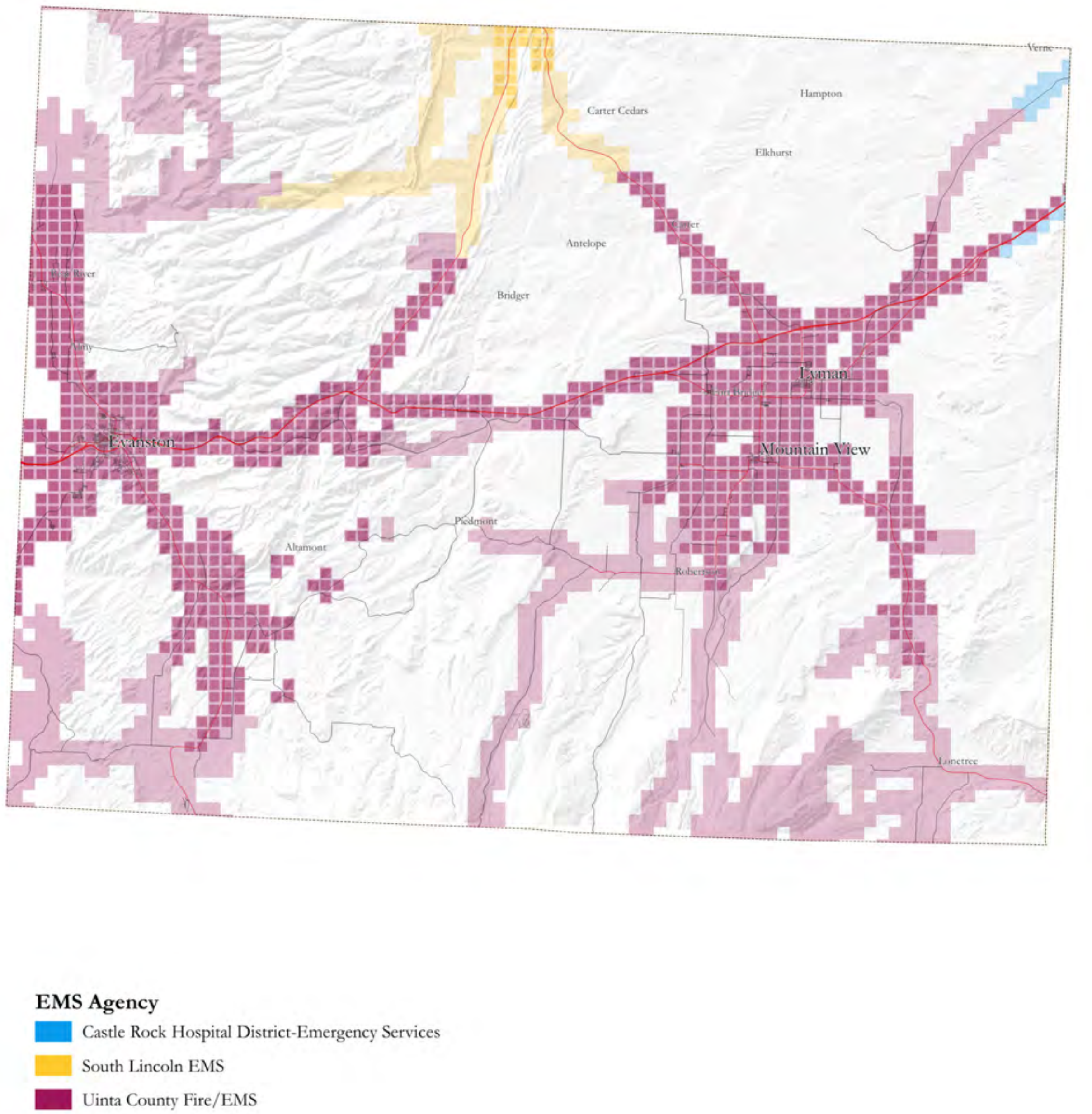
EMS Agency

- Carbon County EMS
- Castle Rock Hospital District-Emergency Services
- Eden Farson Fire District
- Frontier Ambulance
- Little Snake River
- South Central WY Emergency Medical Services
- South Lincoln EMS
- Sublette County EMS
- Uinta County Fire/EMS
- Wamsutter EMS

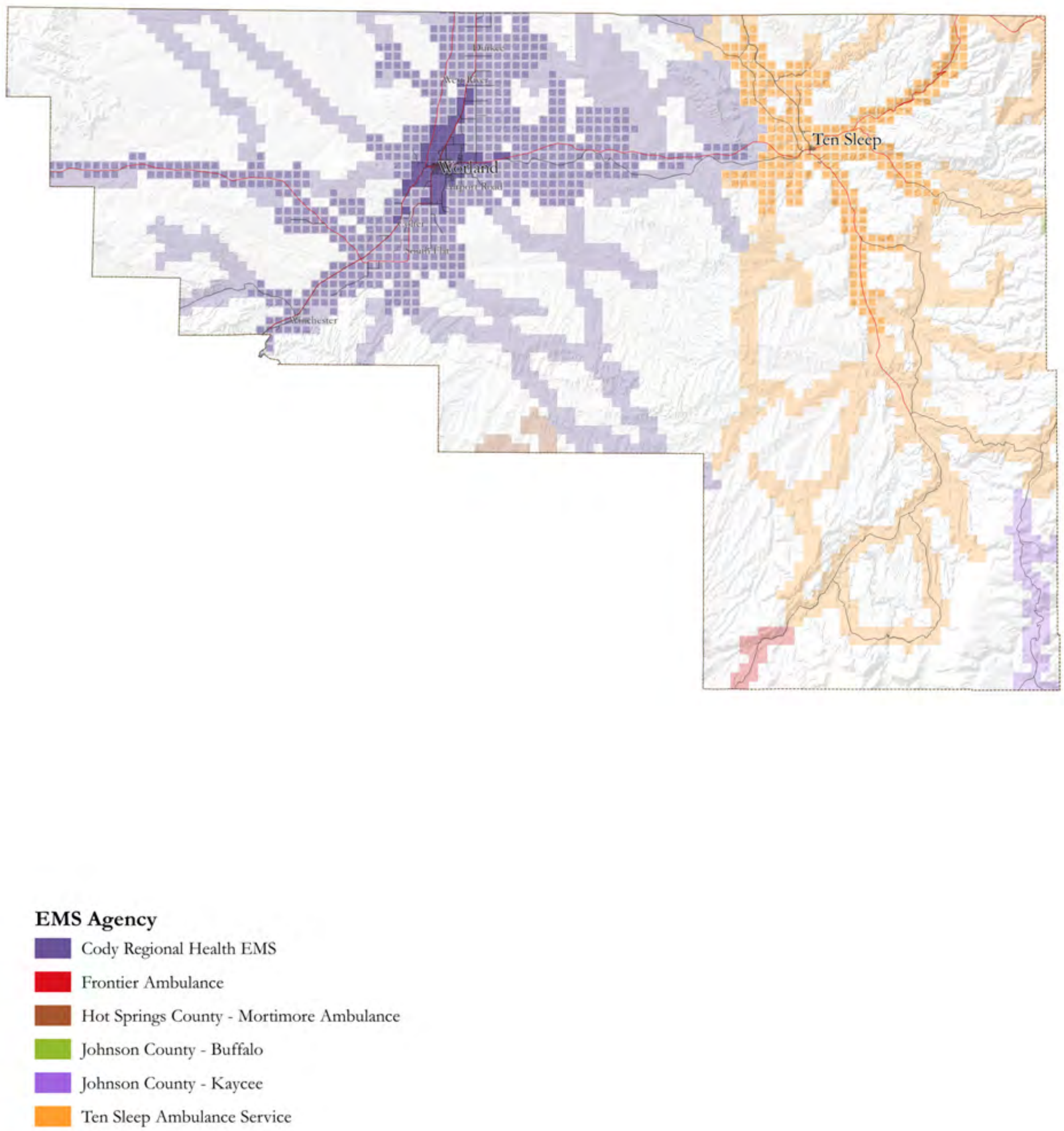
7.1.20 Teton County



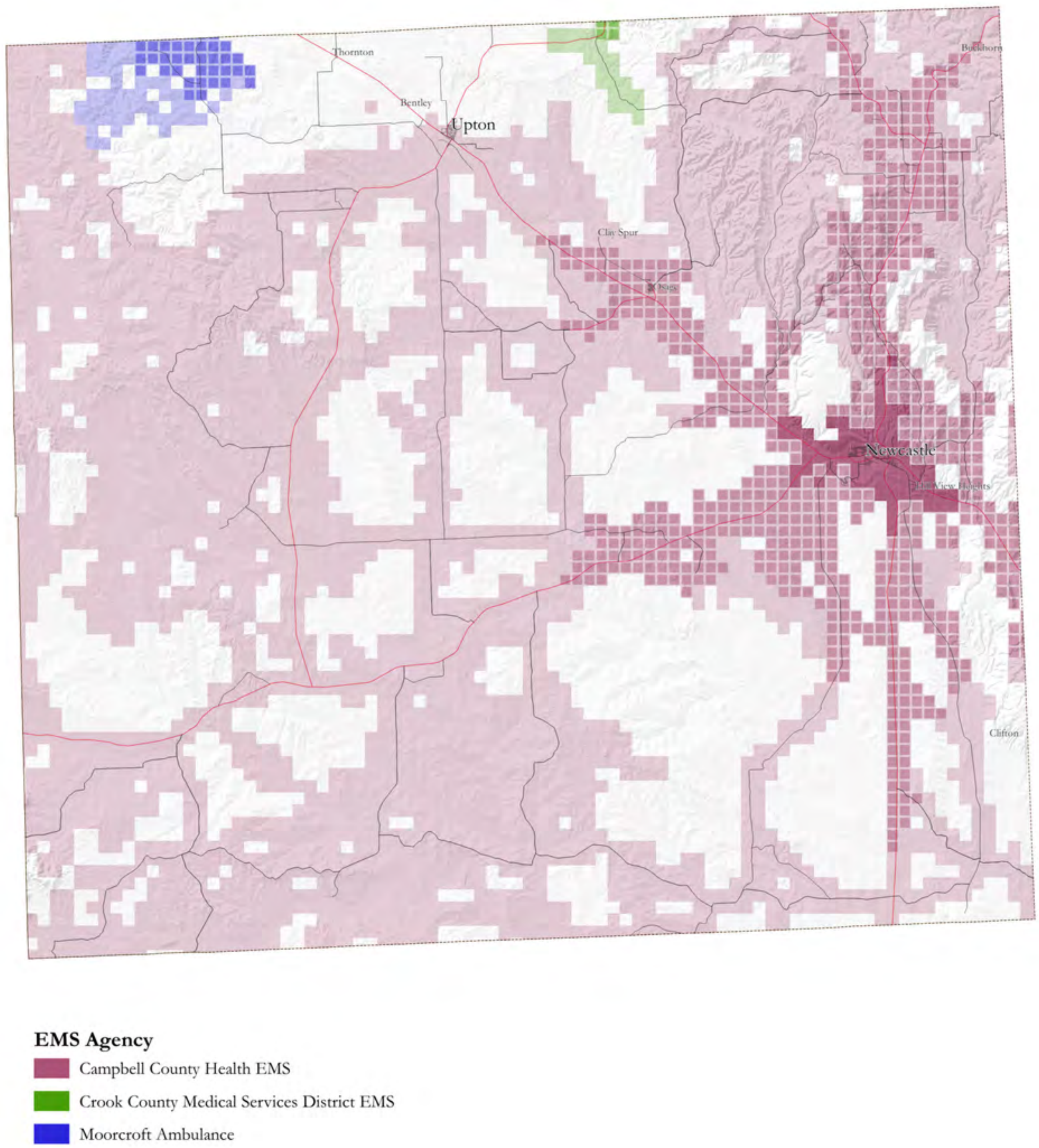
7.1.21 Uinta County



7.1.22 Washakie County



7.1.23 Weston County



7.2 Comparing standardized response times

This section summarizes how all agencies stack up on the most basic measure of service delivery: the expected time it takes for an ambulance to show up to the patient once they've been dispatched.

Since the *actual* response time for each call we observe varies significantly based on agency capabilities, travel time, weather, road conditions, etc., we use a model to first adjust for some of these factors and then estimate the *expected* (or average) response time to what we call a "standard" call —one which occurs precisely at noon in July, and is a 5 minute drive away from the nearest ambulance, according to Google Maps.[50]

We break response time into two components:

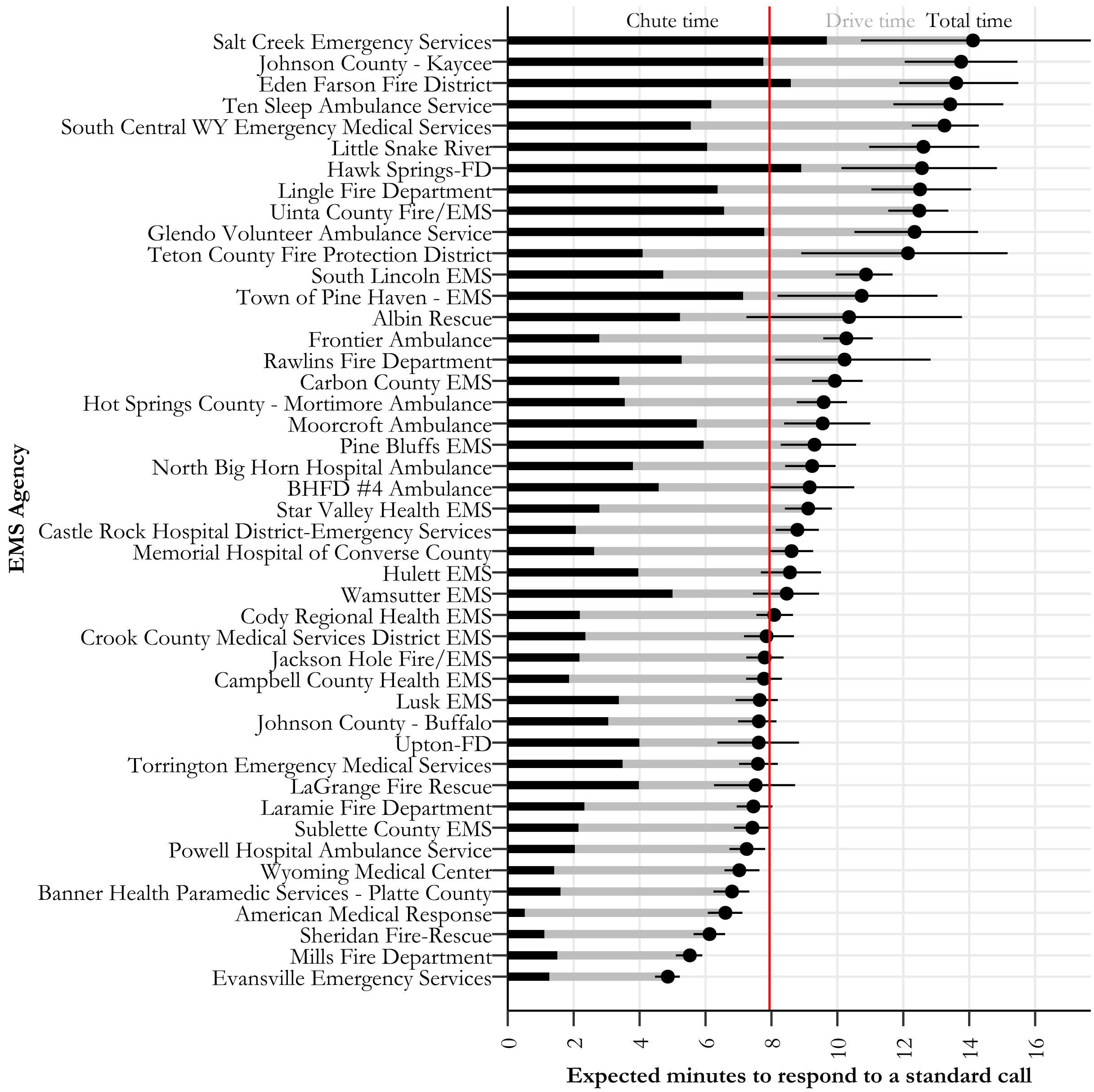
- The **"chute time"** between the call being received and the ambulance getting on the road; and,
- The **drive time** to the destination.

Figure 10 shows how each service compares with the state average (red line). On the figure, the black bar shows the "chute time." The gray bar, stacked on top of the black bar, adds the drive time, and the black point-and-range tacked on the end shows the expected total time (including uncertainty, which increases if we have a smaller observed sample).

Note on the figure that the fastest-responding services tend to be the larger, full-time outfits. Smaller volunteer services in particular tend to have longer "chute times," simply because volunteers aren't sitting around in ambulances all day; they usually have a requirement to get to the ambulance within 10 minutes.

[50]We actually use Open Street Map data, but the concept is the same.

Figure 10: Response times to a standard call



7.3 How many people live in each response time zone?

Given the previous two sections, this is the natural question. To try and answer this, we have to use "gridded" population estimates, which are unfortunately somewhat dated (2010),[51] in our merge with each grid square.

With that caveat, Table 8 estimates the percentage of each county's population that lives within each response time zone. The table is sorted by the population living outside 30+ minutes. As expected, some of the more rural counties (e.g., Crook and Weston), have the largest percentages here, though geographic size and population distribution is a factor (Fremont, Park). There are also some oddities:

- Uinta F.D. serves the entire county and has an expected response time just outside 9 minutes due to a longer chute time. This puts virtually the entire county population in the "9-30 minute" response time category.
- Similarly, counties with a lot of volunteer coverage (e.g. Carbon) have longer chute times that reduce the percentage of folks within the "under 9 minutes" category.

Finally, Table 9 shows the 10 county subdivisions with the largest number of people outside a 30 minute response. Note that many of these are close to urban areas (Cheyenne, Casper, Gillette), but the largest number of people (almost 5,800) in this situation live on the Wind River Reservation.

[51] Using a previously-downloaded version of the Socioeconomic Data and Applications Center (SEDAC) - Gridded Population of the World, administrative center data points, which are no longer accessible at: https://www.earthdata.nasa.gov/data/catalog/sedac-ciesin-sedac-gpwv4-aducppe-r11-4.11

Table 8: Percent of Wyoming's population by response time

	Expected response time		
County	**< 9 min.**	**9 - 30 min.**	**30+ min.**
Washakie	75%	23%	1%
Natrona	70%	27%	3%
Sweetwater	54%	43%	3%
Uinta	0%	97%	3%
Laramie	87%	10%	3%
Albany	88%	8%	4%
Carbon	4%	92%	4%
Platte	75%	21%	4%
Goshen	70%	26%	4%
Teton	73%	22%	5%
Lincoln	21%	75%	5%
Big Horn	34%	61%	5%
Hot Springs	45%	49%	6%
Sheridan	62%	32%	6%
Campbell	59%	34%	7%
Converse	67%	25%	7%
Sublette	48%	44%	7%
Johnson	66%	26%	8%
Park	58%	33%	8%
Niobrara	68%	18%	15%
Fremont	6%	75%	19%
Crook	34%	41%	25%
Weston	59%	15%	26%
State average	**58%**	**36%**	**6%**

Table 9: County subdivisions with the most people outside 30 minutes

	Expected response time		
County subdivision	**< 9 min.**	**9 - 30 min.**	**30+ min.**
Pine Bluffs	903	1,532	944
Casper North	953	3,578	986
Cheyenne West	3,907	2,319	1,028
Moorcroft	602	1,512	1,156
Cheyenne East	2,515	4,924	1,203
Gillette South	5,600	8,307	1,371
Upton	12	23	1,477
Cody	8,211	5,673	1,764
Gillette North	21,640	7,403	1,812
Wind River Reservation	429	20,309	5,747

8 EMS operations and financial sustainability

This section provides a statewide overview of the costs and revenue situations of ground EMS services.

It begins with a summary of the registered ambulances and active (2024) staff at each EMS service, just to provide an overview of the available capital and labor.

We then try to estimate the **reasonable cost** of those resources based on a specific readiness estimate.

Then, we compare the potential **service revenue** that is available to pay for that reasonable cost.

As we describe in later sections, both the cost and revenue estimates are just that: estimates, based on available data and leaning heavily on statistical models. We do not have access to standardized cost and revenue data from EMS agencies,[52] though we interviewed EMS agencies in the course of developing this report and received feedback as to whether estimates are in the ballpark.

Nonetheless, we believe these costs and revenue numbers are good enough to conclude that: (1) only the largest services are viable based on billing alone, and (2) the net income gap for most services in Wyoming must be filled by some kind of subsidy.

8.1 Total vehicles and staffing

Table 10 shows the count of registered ambulances and active (e.g., responded to at least one call in 2024) staff by type, for all Wyoming ground services.

Table 10: Active vehicles and staff, 2024

		Staff				
Agency	**Vehicles**	**EMR / EMT**	**Paramedic / Firefighter**	**Other**	**Volunteer %**	**Est. hourly labor cost**
Albin Rescue	1	2	0	3	100%	$15.52
American Medical Response	18	44	44	1	0%	$29.16
BHFD #4 Ambulance	1	0	15	0	87%	$13.06
Banner Health - Platte County	7	13	15	2	0%	$25.36
Campbell County Health EMS	19	44	44	9	0%	$28.11
Carbon County EMS	4	13	5	8	0%	$27.62
Castle Rock Hospital -EMS	8	26	8	6	0%	$26.33
Cody Regional Health EMS	19	26	32	9	0%	$27.31
Crook County EMS	3	4	8	17	0%	$33.94
Eden Farson Fire	2	0	20	0	80%	$14.70

[52] This has been attempted on the federal side by a decades-long effort to implement the Ground Ambulance Data Collection System, but data is not publicly-available and the first report from this effort was released only in December 2024. ("Medicare Ground Ambulance Data Collection System (GADCS) Report - Year 1 and Year 2 Cohort Analysis." RAND Health Care. PR-A2743-7.)

Table 10: Active vehicles and staff, 2024 *(continued)*

Agency	Vehicles	Staff				
		EMR / EMT	Paramedic / Firefighter	Other	Volunteer %	Est. hourly labor cost
Evansville EMS	5	19	4	9	9%	$28.45
Frontier Ambulance	14	28	14	1	0%	$25.59
Glendo Volunteer Ambulance	1	9	1	1	55%	$16.43
Hawk Springs-FD	2	0	13	0	77%	$15.25
Hot Springs County - Mortimore	3	13	1	7	0%	$24.77
Hulett EMS	2	3	4	1	44%	$20.41
Jackson Hole Fire/EMS	6	0	84	0	6%	$54.55
Johnson County - Buffalo	5	18	1	22	0%	$26.70
Johnson County - Kaycee	3	7	2	3	62%	$16.08
LaGrange Fire Rescue	3	0	17	0	76%	$15.33
Laramie FD	10	0	89	0	0%	$31.53
Lingle FD	1	0	15	0	93%	$11.50
Little Snake River	2	7	5	2	60%	$15.44
Lusk EMS	3	8	0	8	94%	$12.38
Memorial Hospital of Converse County	7	10	22	6	0%	$29.05
Mills FD	3	0	21	0	0%	$30.57
Moorcroft Ambulance	2	8	3	9	30%	$32.52
North Big Horn Hospital Ambulance	3	9	5	8	0%	$28.04
Pine Bluffs EMS	2	4	1	9	72%	$16.81
Powell Hospital Ambulance	5	15	15	8	0%	$27.99
Rawlins FD	4	0	14	0	0%	$29.92
Salt Creek EMS	2	8	0	0	88%	$9.63
Sheridan Fire-Rescue	3	0	20	0	0%	$32.18
South Central WY EMS	7	11	6	17	90%	$13.52
South Lincoln EMS	5	21	1	7	0%	$25.36
Star Valley Health EMS	8	15	16	6	5%	$32.45
Sublette County EMS	8	24	9	4	0%	$26.97
Ten Sleep Ambulance	2	7	0	8	69%	$15.54
Torrington EMS	4	17	1	10	0%	$20.75
Town of Pine Haven - EMS	1	3	0	2	60%	$13.39
Uinta County Fire/EMS	8	0	77	0	1%	$29.36
Upton-FD	2	0	14	0	71%	$16.05
Wamsutter EMS	3	7	0	2	27%	$24.03
Wyoming Medical Center	10	25	32	6	0%	$29.09
Statewide	**231**	**468**	**698**	**211**	**14%**	**$27.55**

8.2 Average labor cost estimates

The last column of the previous table shows our estimates of the weighted average hourly labor cost for each service. This number is used to estimate reasonable costs in the next section, and includes the following adjustments:

- Employee credential mix (e.g. EMR/EMT/Paramedic);
- Benefit load;
- Geographic cost of living; and,
- Volunteer adjustment.

We start with the most recent Wyoming-specific occupational wage data from the Bureau of Labor Statistics.[53] For the following staff types, we use the following classifications and assumptions:

- **EMR** - assume 85% of EMT - $15.10/hr
- **EMT** (29-2042) - $17.75/hr
- **Paramedic** (29-2043) - $25.22/hr
- **Firefighter** (33-2011) - $24.75/hr
- **Other** - use RN (29-1141) - $40.23/hr

We then blend these wages together for each agency by calculating what fraction of an agency's calls were responded to by each staff type, and multiplying that weight by the respective wage.

For example, if one agency had 160 total calls, and paramedics responded to 100 calls, EMTs responded to 50 calls, and EMRs responded to 10 calls, the blended wage would be $22.25, since:

$$22.25 = (25.22 \times \frac{100}{160}) + (17.75 \times \frac{50}{160}) + (15.10 \times \frac{10}{160})$$

Then, we use county cost of living adjustments developed by the Wyoming Department of Administration and Information Economic Analysis Division[54] to adjust wages based on the locations of each ambulance service.

Finally, we adjust costs based on the proportion of volunteers at each service. Our best estimate is that most volunteers are paid to be on-call (e.g., within a 10 minute arrival to the ambulance) at a stipend around half that of professional staff wages. They also likely do not receive benefits.[55]

8.3 Estimated reasonable costs

As noted previously, we don't have actual cost or revenue data for ambulance services.

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[53] May 2023, https://www.bls.gov/oes/current/oes_wy.htm

[54] https://drive.google.com/file/d/1BVSGHsZjSEaUk6ZJnFQzmoyhQUMPER94/view

[55] Where professional staff cost an ambulance service the geographically-adjusted wage (w) loaded with benefits (we use a factor of 1.3), a volunteer would cost the wage times the volunteer factor (0.5) and no benefits. Depending on its overall percent of volunteers (v), an ambulance service's average labor costs are therefore: $v(0.5w) + (1 - v)(1.3w)$, which simplifies to $0.5vw + 1.3w - 1.3vw$ and further to $w(1.3 - 0.8v)$. This gets us to the final estimated hourly labor cost shown in the last column.

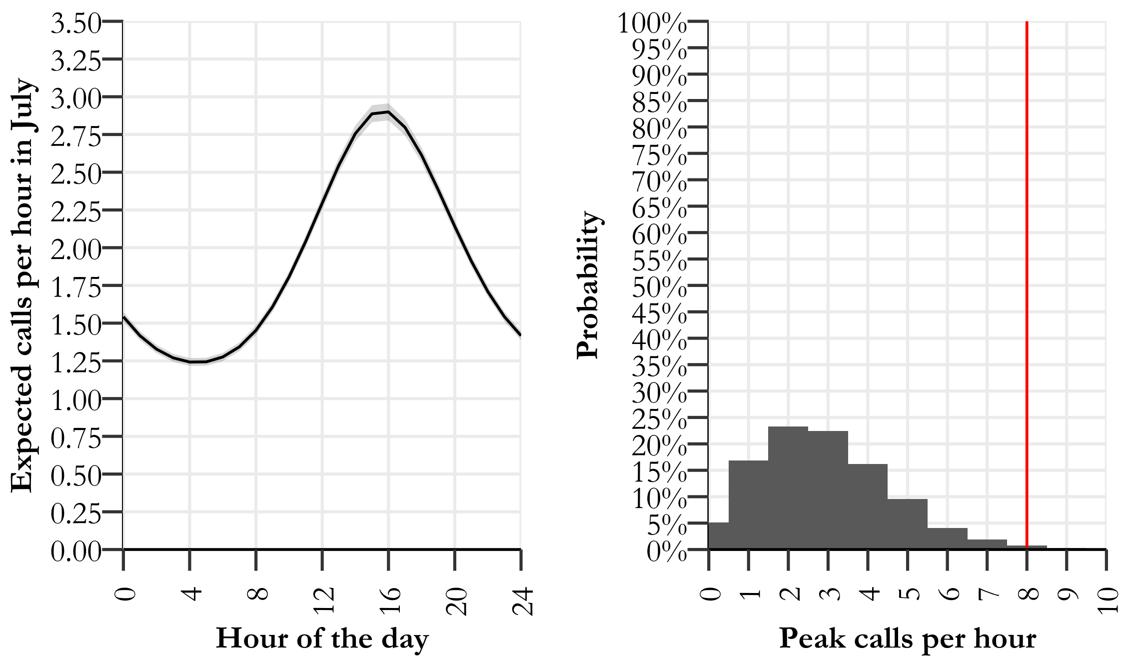
Our approach here is therefore to define a **reasonable cost** based on the required number of ambulances a service would be expected to maintain in readiness at any given time, then calculate the costs to staff that ambulance, and finally extrapolate total costs from there.

8.3.1 Reasonable costs are based on readiness requirements

We define this readiness requirement as the average of the peak and off-peak demand, which we estimate using WATRS data grouped into 30-minute time segments.

Figure 11 shows how this demand signal varies over time for one of the larger agencies, American Medical Response (AMR) in Cheyenne.

Figure 11: Demand, American Medical Response



Here, the panel on the left side of the figure shows how the expected number of calls varies by the hour of the day during the peak month (July). As one would expect, demand is lowest in the early morning (1.25 expected calls/hour at 0400) and then peaks in the afternoon (2.9 expected calls/hour at 1600).

Expected demand, however, is just an average. Calls come in randomly distributed around that average, so actual volume could be significantly higher or lower. The panel on the right shows the distribution of calls at AMR's peak time. From this, we know that AMR can expect to service anywhere between 0 and 8 simultaneous calls between 1600 and 1630 on a day in July. The red line shows the 99th percentile of 8 simultaneous calls, a reasonable standard for readiness.

8.3.2 Sidenote: utilization pays for readiness

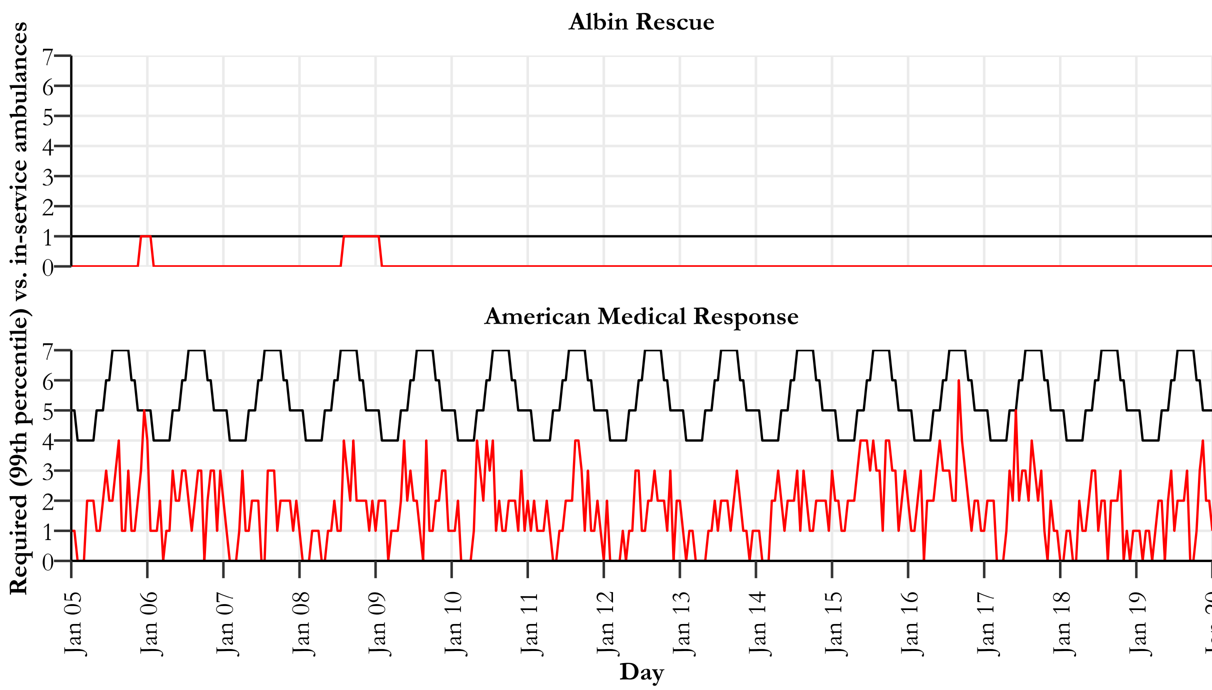
Generally speaking, larger services with more volume will be able to "pay for" the cost of readiness by working their ambulances more frequently.

To give a concrete example, let's consider two services —AMR and Albin Rescue —which both serve Laramie County, but at dramatically different scale.

Figure 12 shows demand over a random 15-day interval in January 2024. The black lines on each plot show how many ambulances need to be ready to go to handle calls at the 99th percentile service level. The red lines show how many ambulances were actually out on a call at any given time. Note that:

- Albin Rescue requires 1 ambulance, but only serviced 2 calls during those 15 days.
- AMR requires between 4-7 ambulances (assuming scheduling tracks average hourly demand fluctuations), but usually had around 1-3 ambulances running calls at any given time, though there was a time on January 16th when 6 ambulances were necessary.

Figure 12: Required vs. in-service ambulance example



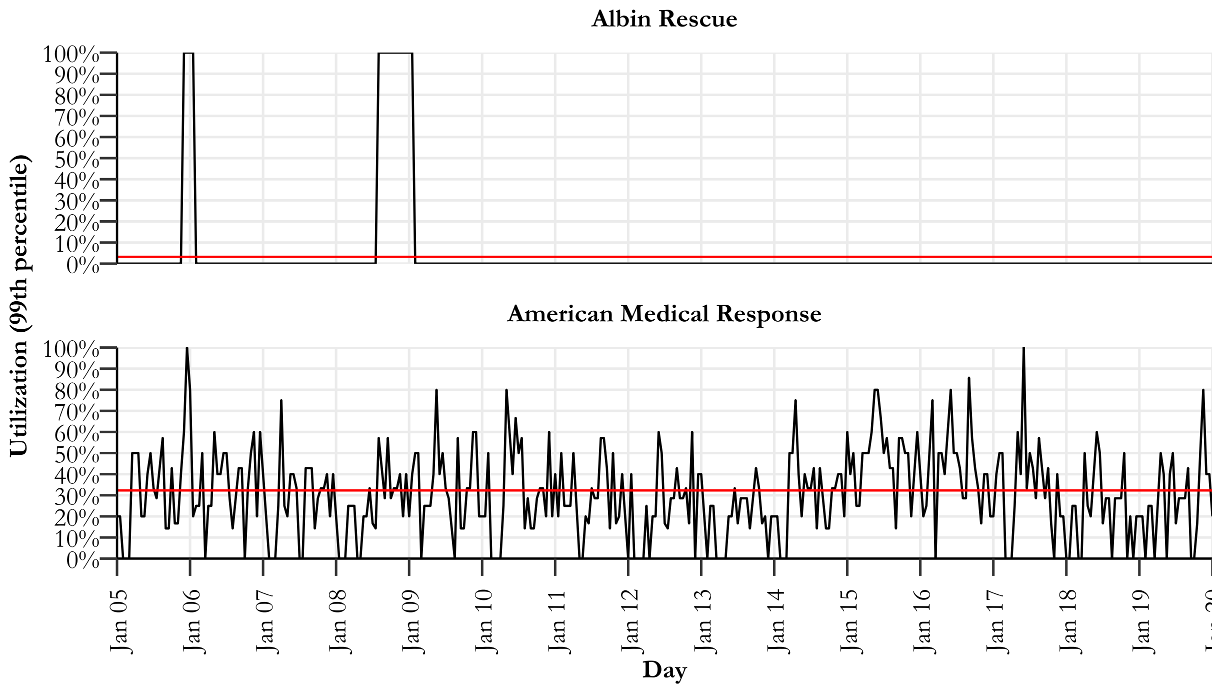
When we divide the actual in-service ambulances (red) by the required ready ambulances (black), we get a measure called "utilization", which refers to the average load on an ambulance service. On Figure 13, we can see Albin Rescue's and AMR's utilization for the same 15-day window (black lines). We have overlaid a red line indicating their average utilization for the entire year: AMR at ~ 32% and Albin at around 5%.

The larger the volume, the higher utilization can be. At some point however, high utilization can become a problem; while efficient, it reduces a service's ability to handle peak demand. Most services nationally prefer to keep utilization in the 30-50% range. This is not an issue for any service in Wyoming.

When we do this exercise for all services, we can compare utilization across the State in Figure 14. Note:

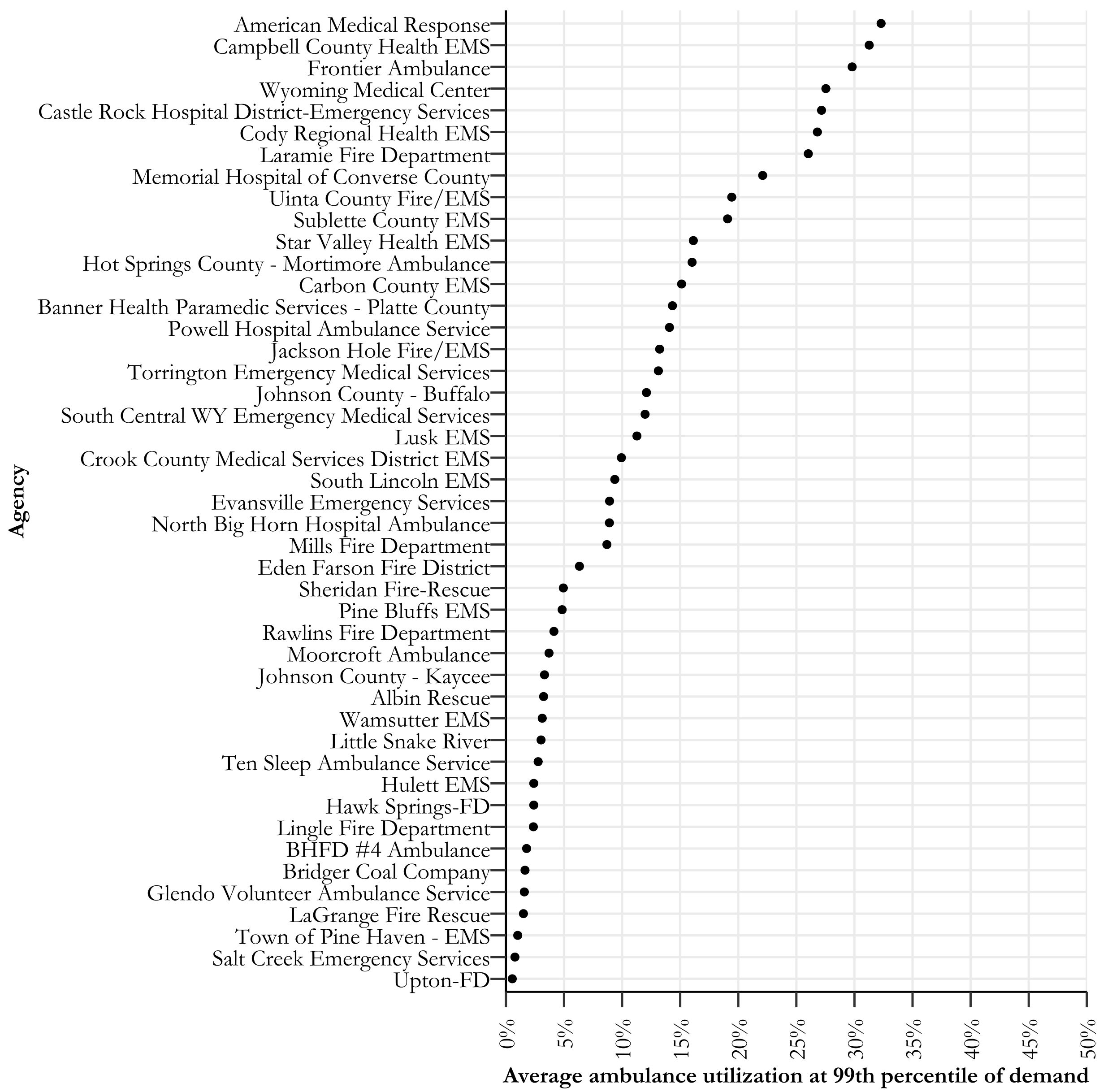
- Only three (3) of the largest services have utilization at or above 30%;

Figure 13: Point-in-time vs. average utilization



- Utilization correlates with economic viability. The more efficient a service is, the more existing payer rates can cover costs.
- Volunteer business models make more sense when utilization is low; instead of paying full-time staff to sit in a parked ambulance 95% of the time, volunteers can go about their day job (usually within 10 minutes of the ambulance). Aside from the decline in volunteerism, the main downside to this model is increased chute times.

Figure 14: Average utilization by service



8.3.3 Extrapolating total costs

Once we have the required number of ambulances each service should reasonably make available 24/7/365, we can estimate the required annual labor costs using the adjusted hourly labor cost derived previously in the following formula:

$$\frac{\text{Labor cost}}{\text{year}} = \text{Req. ambs} \times \frac{\text{2 workers}}{\text{amb.}} \times \frac{\text{365 days}}{\text{year}} \times \frac{\text{24 hours}}{\text{day}} \times \frac{\text{Est. labor cost}}{\text{worker-hour}}$$

From here, we can extrapolate required **total costs** using national data. In the first Ground Ambulance Data Collection System (GADCS) report from December 2024, Table 5.1 on page 128 shows that, for "super-rural" EMS agencies:

- **Labor** costs make up an average of 62.5% of the total;
- **Facility** costs make up 4.4%;
- **Vehicles** make up 14.0%; and,
- **Equipment and other** costs are the remaining 19.1%.

So, to get an approximation of total costs, we can divide the labor cost by 62.5%. This oversimplifies reality, since fixed costs likely do not scale at the same rate as labor, and lower average-wage labor costs do not necessarily reduce vehicle or facility costs. With these simplification in mind, Table 11 below shows how the required ambulances translate into the estimated costs for each service.

Albin Rescue, for example, requires 1 ambulance. While they only responded to 18 calls in 2024, that ambulance has to be ready to go at any time. And at their estimated average wage, that ambulance costs ~$435K to operate. Much of this, importantly, is not actually paid by anyone, but is absorbed by the subsidized labor of volunteers.

AMR, the next line in the table, uses paid labor, so the costs are more tangible. Here, we estimate that 4-8 ambulances are required to service Cheyenne. We estimate the costs of those 4-8 ambulances at around $4.9 million.

At the bottom of the table, we total up the peak and off-peak ambulances, as well as the estimated total cost for the entire State.

Table 11: SFY24 estimated annual costs

	Required ambulances, based on ...		
Agency	**Peak demand**	**Off-peak demand**	**Est. cost**
Albin Rescue	1	1	$435,180
American Medical Response	8	4	$4,904,456
BHFD #4 Ambulance	1	1	$366,183
Banner Health Paramedic Services - Platte County	3	2	$1,777,151
Campbell County Health EMS	8	4	$4,727,325
Carbon County EMS	3	2	$1,935,522

Table 11: SFY24 estimated annual costs *(continued)*

	Required ambulances, based on ...		
Agency	**Peak demand**	**Off-peak demand**	**Est. cost**
Castle Rock Hospital District-Emergency Services	6	3	$3,321,229
Cody Regional Health EMS	6	3	$3,444,892
Crook County Medical Services District EMS	2	1	$1,426,965
Eden Farson Fire District	2	1	$618,169
Evansville Emergency Services	2	1	$1,196,383
Frontier Ambulance	6	4	$3,586,123
Glendo Volunteer Ambulance Service	1	1	$460,586
Hawk Springs-FD	1	1	$427,483
Hot Springs County - Mortimore Ambulance	2	2	$1,388,701
Hulett EMS	1	1	$572,102
Jackson Hole Fire/EMS	2	1	$2,293,875
Johnson County - Buffalo	3	1	$1,497,148
Johnson County - Kaycee	1	1	$450,853
LaGrange Fire Rescue	1	1	$429,743
Laramie Fire Department	5	3	$3,535,564
Lingle Fire Department	1	1	$322,475
Little Snake River	1	1	$432,823
Lusk EMS	2	1	$520,350
Memorial Hospital of Converse County	4	2	$2,442,594
Mills Fire Department	2	1	$1,285,250
Moorcroft Ambulance	1	1	$911,504
North Big Horn Hospital Ambulance	2	1	$1,179,212
Pine Bluffs EMS	1	1	$471,176
Powell Hospital Ambulance Service	3	2	$1,961,827
Rawlins Fire Department	1	1	$838,795
Salt Creek Emergency Services	1	1	$269,978
Sheridan Fire-Rescue	1	1	$901,930
South Central WY Emergency Medical Services	2	1	$568,375
South Lincoln EMS	2	1	$1,066,511
Star Valley Health EMS	3	2	$2,274,342
Sublette County EMS	4	2	$2,268,014
Ten Sleep Ambulance Service	1	1	$435,601
Torrington Emergency Medical Services	3	2	$1,454,169
Town of Pine Haven - EMS	1	1	$375,330
Uinta County Fire/EMS	4	2	$2,469,431
Upton-FD	1	1	$449,875
Wamsutter EMS	1	1	$673,682

Table 11: SFY24 estimated annual costs *(continued)*

	Required ambulances, based on ...		
Agency	**Peak demand**	**Off-peak demand**	**Est. cost**
Wyoming Medical Center	6	4	$4,076,663
Statewide	**113**	**71**	**$66,445,539**

8.4 Maximum potential revenue

Now that we've looked at the cost side of the equation, let's estimate the *maximum potential revenue* that each agency could receive by billing private and public payers. To do this, we combine four pieces of information:

- **EMS call volume**, with available detail on the type of service, EMS agency, geography, and some demographic information (age/sex/race) on patients. This is largely available in WATRS.
- **Rates** that payers would likely pay per trip. We use Medicaid claims data to get the average paid by Medicaid and Medicare (received for Medicare Savings Program Medicaid members), inclusive of mileage. For other public and private payers, we make assumptions about how they compare with Medicare.
- **Insurance coverage**. We recently completed some work with the US Census Bureau using restricted American Community Survey (ACS) microdata to estimate insurance coverage probabilities at a very granular level (Census Block Group, age/race/sex demographic cells). This EMS report is the first application of these estimates.
- **Ambulance risk**. As illustrated in the demographics section, not everyone has an equal chance of needing an ambulance. So, in order to apply the insurance coverage estimates to the WATRS data, we needed to weight them based on ambulance risk. We use Medicaid claims data, combined with Medical Expenditure Panel Survey (MEPS) data to model this risk by payer and demographic cell.

We have more details on how these come together in the technical appendix.

8.4.1 Payer rates

Starting with rates, Table 12, shows how we developed average rates paid by payer, with the "Source" column showing our assumptions.[56] The rates shown are **inclusive of mileage**, based on Wyoming Medicaid claims data.

Table 12: Estimated average rates paid, inclusive of mileage

	911 Response		Transport		
Payer	**ALS**	**BLS**	**ALS**	**BLS**	**Source**
Indian Health Services	$0.00	$0.00	$0.00	$0.00	No recent payments
Medicaid	$349.60	$280.67	$472.67	$293.00	Claims data
Medicare	$754.53	$576.24	$1,217.29	$574.02	Claims data
Medicare + Medicaid dual	$586.13	$452.79	$896.97	$443.33	Claims data
Non-reimbursable	$0.00	$0.00	$0.00	$0.00	Not billiable
Private (directly-purchased)	$1,244.97	$950.80	$2,008.53	$947.13	165% of Medicare

[56] For example, we assume private pay rates are 165% of Medicare, based on a 2024 study from the Health Care Cost Institute (https://healthcostinstitute.org/hcci-originals-dropdown/all-hcci-reports/commercial-prices-for-ground-ambulance-are-double-medicare-rates) and a Medicaid rate benchmarking study.

Table 12: Estimated average rates paid, inclusive of mileage *(continued)*

Payer	ALS	BLS	ALS	BLS	Source
Private (employer-sponsored)	$1,244.97	$950.80	$2,008.53	$947.13	165% of Medicare
TRICARE or VA	$586.13	$452.79	$896.97	$443.33	Assume same as Medicare
Uninsured (< 200% FPL)	$226.36	$172.87	$365.19	$172.21	Assume 30% of Medicare collected
Uninsured (>= 200% FPL)	$603.62	$460.99	$973.83	$459.21	Assume 80% of Medicare collected
Unknown	$0.00	$0.00	$0.00	$0.00	

8.4.2 Payer mix and revenue

If we make the assumption that **every call is billed** and **most payers pay** (to the extent is reasonable; see the notes on uninsured in Table 12), then we can estimate the theoretical maximum revenue potential for each agency, based on calls reported to WATRS.

Table 13 shows the results from this exercise. The first column shows the total reimbursable calls. As we noted previously, EMS agencies cannot bill if they do not transport. In the first row, Albin Rescue, for example, responded to 18 calls in 2024, but only 8 could potentially be billed for. Given their payer mix (largely Medicare), those 18 calls might translate into ~$5,125 of revenue. The uncertainty in the payer mix means it would likely be between $3,664 and $5,985.

Table 13: SFY24 reimbursable calls and maximum potential revenue

		Revenue potential	
Agency	Reimbursable calls	Estimate	Range
Albin Rescue	8	$5,125	[$3,664 - $5,985]
American Medical Response	9,949	$7,036,297	[$6,785,809 - $7,227,698]
BHFD #4 Ambulance	26	$16,478	[$13,715 - $18,279]
Banner Health - Platte County	942	$687,996	[$651,301 - $719,285]
Campbell County Health EMS	6,767	$5,043,674	[$4,942,968 - $5,189,997]
Carbon County EMS	818	$648,432	[$595,718 - $680,091]
Castle Rock Hospital -EMS	2,943	$2,316,913	[$2,237,675 - $2,382,378]
Cody Regional Health EMS	2,831	$2,022,667	[$1,967,550 - $2,081,436]
Crook County EMS	251	$198,536	[$183,167 - $212,551]
Eden Farson Fire	41	$31,643	[$29,501 - $35,729]
Evansville EMS	391	$300,781	[$285,434 - $312,081]
Frontier Ambulance	4,743	$2,643,721	[$2,493,816 - $2,824,300]
Glendo Volunteer Ambulance	29	$20,676	[$17,271 - $24,425]
Hawk Springs-FD	27	$19,349	[$15,994 - $22,225]
Hot Springs County - Mortimore	471	$306,947	[$289,605 - $337,832]
Hulett EMS	64	$47,706	[$45,019 - $51,296]

Table 13: SFY24 reimbursable calls and maximum potential revenue *(continued)*

		Revenue potential	
Agency	**Reimbursable calls**	**Estimate**	**Range**
Jackson Hole Fire/EMS	896	$734,717	[$712,326 - $772,455]
Johnson County - Buffalo	581	$424,274	[$391,929 - $441,579]
Johnson County - Kaycee	45	$31,951	[$29,114 - $35,359]
LaGrange Fire Rescue	27	$16,519	[$14,391 - $19,814]
Laramie FD	2,456	$1,928,788	[$1,829,762 - $1,993,657]
Lingle FD	52	$32,171	[$29,049 - $34,751]
Little Snake River	43	$31,877	[$26,910 - $35,701]
Lusk EMS	230	$138,915	[$122,548 - $159,576]
Memorial Hospital of Converse County	1,279	$995,001	[$925,647 - $1,036,152]
Mills FD	440	$307,674	[$289,546 - $330,805]
Moorcroft Ambulance	45	$35,822	[$30,769 - $38,294]
North Big Horn Hospital Ambulance	282	$205,100	[$191,442 - $219,752]
Pine Bluffs EMS	72	$53,246	[$47,129 - $57,111]
Powell Hospital Ambulance	875	$636,240	[$609,706 - $670,200]
Rawlins FD	19	$14,915	[$12,027 - $18,022]
Salt Creek EMS	6	$3,724	[$2,792 - $4,458]
Sheridan Fire-Rescue	2	$1,222	[$1,029 - $1,341]
South Central WY EMS	347	$272,722	[$257,929 - $282,319]
South Lincoln EMS	234	$181,498	[$167,076 - $193,251]
Star Valley Health EMS	720	$566,440	[$545,761 - $581,292]
Sublette County EMS	726	$594,114	[$571,480 - $618,166]
Ten Sleep Ambulance	49	$33,621	[$28,108 - $38,539]
Torrington EMS	893	$635,969	[$607,990 - $664,449]
Town of Pine Haven - EMS	17	$10,724	[$9,588 - $11,545]
Uinta County Fire/EMS	1,372	$982,454	[$923,962 - $1,028,032]
Upton-FD	10	$6,608	[$5,854 - $7,788]
Wamsutter EMS	36	$30,043	[$25,280 - $35,220]
Wyoming Medical Center	8,801	$6,364,433	[$6,165,396 - $6,576,685]
Statewide	**50,856**	**$36,617,722**	**[$36,254,583 - $37,039,100]**

8.5 Bottom line: costs vs. revenue

The bottom line, for the purposes of this report, is the *required subsidy*: the delta between the reasonable costs of service and the theoretical maximum that can be billed.

Generally speaking, this subsidy correlates with volume. In order to pay for ambulances in readiness, each ambulance has to respond to a certain minimum number of calls. When that volume is lower than required, which is the case throughout most of Wyoming, some kind of subsidy is necessary. As previously noted, it can take many forms —tax dollars, enhanced Medicare payments (e.g. Critical Access Hospitals), volunteer labor —but it ultimately must be paid for a service to be viable.

Table 14 shows costs, revenue, and this required subsidy as a percent of operating costs, by agency.

Table 14: SFY24 Est. costs, revenue, and required subsidy

			Est. required subsidy	
Agency	**Est. total cost**	**Est. revenue potential**	**($)**	**(%)**
Albin Rescue	$435,180	$5,125	$430,055	99%
American Medical Response	$4,904,456	$7,036,297	-$2,131,841	-43%
BHFD #4 Ambulance	$366,183	$16,478	$349,705	96%
Banner Health Paramedic Services - Platte County	$1,777,151	$687,996	$1,089,155	61%
Campbell County Health EMS	$4,727,325	$5,043,674	-$316,349	-7%
Carbon County EMS	$1,935,522	$648,432	$1,287,090	66%
Castle Rock Hospital District-Emergency Services	$3,321,229	$2,316,913	$1,004,315	30%
Cody Regional Health EMS	$3,444,892	$2,022,667	$1,422,225	41%
Crook County Medical Services District EMS	$1,426,965	$198,536	$1,228,429	86%
Eden Farson Fire District	$618,169	$31,643	$586,526	95%
Evansville Emergency Services	$1,196,383	$300,781	$895,601	75%
Frontier Ambulance	$3,586,123	$2,643,721	$942,402	26%
Glendo Volunteer Ambulance Service	$460,586	$20,676	$439,909	96%
Hawk Springs-FD	$427,483	$19,349	$408,133	95%
Hot Springs County - Mortimore Ambulance	$1,388,701	$306,947	$1,081,754	78%
Hulett EMS	$572,102	$47,706	$524,397	92%
Jackson Hole Fire/EMS	$2,293,875	$734,717	$1,559,157	68%
Johnson County - Buffalo	$1,497,148	$424,274	$1,072,874	72%
Johnson County - Kaycee	$450,853	$31,951	$418,902	93%
LaGrange Fire Rescue	$429,743	$16,519	$413,224	96%
Laramie Fire Department	$3,535,564	$1,928,788	$1,606,777	45%
Lingle Fire Department	$322,475	$32,171	$290,304	90%
Little Snake River	$432,823	$31,877	$400,946	93%
Lusk EMS	$520,350	$138,915	$381,435	73%
Memorial Hospital of Converse County	$2,442,594	$995,001	$1,447,593	59%
Mills Fire Department	$1,285,250	$307,674	$977,576	76%

Table 14: SFY24 Est. costs, revenue, and required subsidy *(continued)*

Agency	Est. total cost	Est. revenue potential	Est. required subsidy ($)	(%)
Moorcroft Ambulance	$911,504	$35,822	$875,681	96%
North Big Horn Hospital Ambulance	$1,179,212	$205,100	$974,112	83%
Pine Bluffs EMS	$471,176	$53,246	$417,930	89%
Powell Hospital Ambulance Service	$1,961,827	$636,240	$1,325,587	68%
Rawlins Fire Department	$838,795	$14,915	$823,880	98%
Salt Creek Emergency Services	$269,978	$3,724	$266,254	99%
Sheridan Fire-Rescue	$901,930	$1,222	$900,708	100%
South Central WY Emergency Medical Services	$568,375	$272,722	$295,653	52%
South Lincoln EMS	$1,066,511	$181,498	$885,013	83%
Star Valley Health EMS	$2,274,342	$566,440	$1,707,902	75%
Sublette County EMS	$2,268,014	$594,114	$1,673,900	74%
Ten Sleep Ambulance Service	$435,601	$33,621	$401,980	92%
Torrington Emergency Medical Services	$1,454,169	$635,969	$818,201	56%
Town of Pine Haven - EMS	$375,330	$10,724	$364,606	97%
Uinta County Fire/EMS	$2,469,431	$982,454	$1,486,977	60%
Upton-FD	$449,875	$6,608	$443,266	99%
Wamsutter EMS	$673,682	$30,043	$643,638	96%
Wyoming Medical Center	$4,076,663	$6,364,433	-$2,287,770	-56%
Statewide	**$66,445,539**	**$36,617,722**	**$29,827,816**	**45%**

8.6 Agency detail

This final section looks at call volume, payer mixes, and estimated costs and revenue for each specific agency.

- Each page shows one agency.
- The first table breaks down **total transport volume** by response type and time. The last column on this table is the sum of the preceding four call subtypes (911 responses, interfacility transports, non-reimbursable calls, and unknown).
- The next table estimates the **payer mix** seen by that agency. The first column shows the major payer types, and then the next columns break down payer mix by total volume (i.e., by calls) and by total revenue.
- At the bottom, we have two side-by-side tables, one showing the **required ambulances** (left), and one showing the breakdown of how that requirement translates into **costs**, how those costs are met with **revenue**, and what the **net-income** delta is ("Est. required subsidy")

8.6.1 Albin Rescue

Table 15: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	6	1	17	0	24
2023	8	0	20	0	28
2024	8	0	10	1	19

Table 16: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	3%	[0% - 11%]	3%	[0% - 13%]
Medicare	17%	[0% - 26%]	37%	[0% - 63%]
Medicare + Medicaid dual	7%	[0% - 21%]	13%	[0% - 32%]
Non-reimbursable	53%	[53% - 53%]	0%	[0% - 0%]
Private (directly-purchased)	2%	[0% - 5%]	7%	[0% - 20%]
Private (employer-sponsored)	11%	[0% - 16%]	37%	[0% - 58%]
TRICARE or VA	1%	[0% - 5%]	2%	[0% - 11%]
Uninsured (< 200% FPL)	0%	[0% - 5%]	0%	[0% - 4%]
Uninsured (>= 200% FPL)	0%	[0% - 5%]	1%	[0% - 9%]
Unknown	5%	[5% - 5%]	0%	[0% - 0%]

Table 17: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 18: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$16
Est. labor cost	$271,987
Est. total cost	$435,180
Est. revenue potential	$5,125
Est. required subsidy	$430,055

8.6.2 American Medical Response

Table 19: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	7,510	2,092	4,287	86	13,975
2023	7,679	1,861	4,124	100	13,764
2024	8,010	1,939	4,340	67	14,356

Table 20: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	8%	[6% - 9%]	5%	[4% - 6%]
Medicare	27%	[25% - 30%]	37%	[33% - 40%]
Medicare + Medicaid dual	11%	[8% - 14%]	12%	[8% - 15%]
Non-reimbursable	30%	[30% - 30%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[2% - 5%]	8%	[5% - 11%]
Private (employer-sponsored)	15%	[13% - 17%]	34%	[31% - 37%]
TRICARE or VA	3%	[2% - 4%]	3%	[2% - 4%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 1%]	1%	[0% - 2%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 21: Ambulance requirements

Requirement	Count
Locations	7
Peak demand	8
Off-peak demand	4

Table 22: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$29
Est. labor cost	$3,065,285
Est. total cost	$4,904,456
Est. revenue potential	$7,036,297
Est. required subsidy	-$2,131,841

8.6.3 BHFD #4 Ambulance

Table 23: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	15	5	12	0	32
2023	24	4	23	1	52
2024	26	0	25	0	51

Table 24: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 2%]	0%	[0% - 0%]
Medicaid	6%	[0% - 12%]	5%	[0% - 12%]
Medicare	23%	[10% - 29%]	40%	[20% - 54%]
Medicare + Medicaid dual	6%	[0% - 15%]	8%	[0% - 20%]
Non-reimbursable	46%	[46% - 46%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[0% - 8%]	8%	[0% - 23%]
Private (employer-sponsored)	14%	[2% - 21%]	38%	[14% - 59%]
TRICARE or VA	0%	[0% - 2%]	1%	[0% - 3%]
Uninsured (< 200% FPL)	1%	[0% - 4%]	0%	[0% - 2%]
Uninsured (>= 200% FPL)	1%	[0% - 4%]	1%	[0% - 5%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 25: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 26: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$13
Est. labor cost	$228,865
Est. total cost	$366,183
Est. revenue potential	$16,478
Est. required subsidy	$349,705

8.6.4 Banner Health Paramedic Services - Platte County

Table 27: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	592	291	711	19	1,613
2023	632	302	675	8	1,617
2024	666	276	649	5	1,596

Table 28: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	5%	[3% - 7%]	4%	[2% - 5%]
Medicare	29%	[25% - 32%]	46%	[39% - 51%]
Medicare + Medicaid dual	7%	[5% - 11%]	9%	[5% - 15%]
Non-reimbursable	41%	[41% - 41%]	0%	[0% - 0%]
Private (directly-purchased)	2%	[1% - 4%]	6%	[3% - 9%]
Private (employer-sponsored)	13%	[10% - 15%]	33%	[27% - 40%]
TRICARE or VA	0%	[0% - 1%]	1%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 4%]	2%	[0% - 4%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 29: Ambulance requirements

Requirement	Count
Locations	4
Peak demand	3
Off-peak demand	2

Table 30: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$25
Est. labor cost	$1,110,719
Est. total cost	$1,777,151
Est. revenue potential	$687,996
Est. required subsidy	$1,089,155

8.6.5 Campbell County Health EMS

Table 31: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	2,576	931	1,936	28	5,471
2023	4,369	1,275	2,826	47	8,517
2024	5,194	1,573	3,117	48	9,932

Table 32: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	5%	[4% - 6%]	3%	[2% - 4%]
Medicare	29%	[27% - 31%]	38%	[35% - 40%]
Medicare + Medicaid dual	11%	[9% - 13%]	11%	[9% - 14%]
Non-reimbursable	31%	[31% - 31%]	0%	[0% - 0%]
Private (directly-purchased)	5%	[4% - 6%]	10%	[7% - 13%]
Private (employer-sponsored)	16%	[15% - 19%]	36%	[32% - 40%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 1%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[1% - 1%]	1%	[1% - 1%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 33: Ambulance requirements

Requirement	Count
Locations	4
Peak demand	8
Off-peak demand	4

Table 34: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$28
Est. labor cost	$2,954,578
Est. total cost	$4,727,325
Est. revenue potential	$5,043,674
Est. required subsidy	-$316,349

8.6.6 Carbon County EMS

Table 35: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	520	149	536	21	1,226
2023	594	131	518	21	1,264
2024	686	132	451	16	1,285

Table 36: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	1%	[0% - 1%]	0%	[0% - 0%]
Medicaid	6%	[3% - 8%]	4%	[2% - 5%]
Medicare	23%	[21% - 25%]	30%	[27% - 34%]
Medicare + Medicaid dual	6%	[4% - 8%]	6%	[4% - 9%]
Non-reimbursable	35%	[35% - 35%]	0%	[0% - 0%]
Private (directly-purchased)	2%	[1% - 4%]	5%	[2% - 9%]
Private (employer-sponsored)	24%	[21% - 28%]	53%	[48% - 59%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 2%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 37: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	3
Off-peak demand	2

Table 38: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$28
Est. labor cost	$1,209,701
Est. total cost	$1,935,522
Est. revenue potential	$648,432
Est. required subsidy	$1,287,090

8.6.7 Castle Rock Hospital District-Emergency Services

Table 39: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	710	201	427	28	1,366
2023	1,772	405	976	46	3,199
2024	2,403	540	1,610	44	4,597

Table 40: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	4%	[3% - 6%]	3%	[2% - 4%]
Medicare	27%	[25% - 29%]	36%	[34% - 39%]
Medicare + Medicaid dual	6%	[4% - 7%]	6%	[4% - 8%]
Non-reimbursable	35%	[35% - 35%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[2% - 5%]	7%	[4% - 10%]
Private (employer-sponsored)	21%	[19% - 23%]	47%	[43% - 49%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[1% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 2%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 41: Ambulance requirements

Requirement	Count
Locations	2
Peak demand	6
Off-peak demand	3

Table 42: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$26
Est. labor cost	$2,075,768
Est. total cost	$3,321,229
Est. revenue potential	$2,316,913
Est. required subsidy	$1,004,315

8.6.8 Cody Regional Health EMS

Table 43: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	1,749	901	1,385	68	4,103
2023	1,836	923	1,369	70	4,198
2024	2,050	781	1,340	37	4,208

Table 44: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[3% - 5%]	3%	[2% - 4%]
Medicare	34%	[32% - 37%]	48%	[45% - 51%]
Medicare + Medicaid dual	12%	[10% - 14%]	13%	[10% - 16%]
Non-reimbursable	32%	[32% - 32%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[3% - 5%]	10%	[7% - 12%]
Private (employer-sponsored)	11%	[9% - 12%]	25%	[22% - 28%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[1% - 2%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 45: Ambulance requirements

Requirement	Count
Locations	4
Peak demand	6
Off-peak demand	3

Table 46: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$27
Est. labor cost	$2,153,058
Est. total cost	$3,444,892
Est. revenue potential	$2,022,667
Est. required subsidy	$1,422,225

8.6.9 Crook County Medical Services District EMS

Table 47: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	121	109	120	7	357
2023	142	115	111	12	380
2024	156	95	116	8	375

Table 48: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[1% - 10%]	2%	[1% - 7%]
Medicare	31%	[23% - 37%]	40%	[31% - 49%]
Medicare + Medicaid dual	8%	[1% - 13%]	8%	[2% - 14%]
Non-reimbursable	31%	[31% - 31%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[0% - 8%]	9%	[0% - 16%]
Private (employer-sponsored)	19%	[14% - 23%]	39%	[30% - 47%]
TRICARE or VA	0%	[0% - 3%]	0%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 3%]	1%	[0% - 3%]
Unknown	2%	[2% - 2%]	0%	[0% - 0%]

Table 49: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	2
Off-peak demand	1

Table 50: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$34
Est. labor cost	$891,853
Est. total cost	$1,426,965
Est. revenue potential	$198,536
Est. required subsidy	$1,228,429

8.6.10 Eden Farson Fire District

Table 51: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	34	0	36	2	72
2023	39	0	64	0	103
2024	41	0	42	2	85

Table 52: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	5%	[0% - 9%]	4%	[0% - 8%]
Medicare	19%	[12% - 24%]	29%	[19% - 39%]
Medicare + Medicaid dual	5%	[0% - 13%]	6%	[0% - 17%]
Non-reimbursable	43%	[43% - 43%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[0% - 11%]	10%	[0% - 25%]
Private (employer-sponsored)	19%	[12% - 25%]	48%	[35% - 60%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 4%]	1%	[0% - 2%]
Uninsured (>= 200% FPL)	2%	[0% - 7%]	3%	[0% - 9%]
Unknown	3%	[3% - 3%]	0%	[0% - 0%]

Table 53: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	2
Off-peak demand	1

Table 54: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$15
Est. labor cost	$386,355
Est. total cost	$618,169
Est. revenue potential	$31,643
Est. required subsidy	$586,526

8.6.11 Evansville Emergency Services

Table 55: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	328	37	307	9	681
2023	340	38	254	2	634
2024	304	87	239	3	633

Table 56: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	5%	[3% - 8%]	4%	[2% - 5%]
Medicare	21%	[19% - 23%]	30%	[26% - 34%]
Medicare + Medicaid dual	9%	[6% - 12%]	10%	[6% - 14%]
Non-reimbursable	38%	[38% - 38%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[2% - 6%]	9%	[5% - 14%]
Private (employer-sponsored)	19%	[17% - 23%]	45%	[40% - 52%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 3%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 57: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	2
Off-peak demand	1

Table 58: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$28
Est. labor cost	$747,739
Est. total cost	$1,196,383
Est. revenue potential	$300,781
Est. required subsidy	$895,601

8.6.12 Frontier Ambulance

Table 59: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	3,300	1,419	1,716	157	6,592
2023	3,715	1,109	1,663	128	6,615
2024	3,645	1,098	1,748	108	6,599

Table 60: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	15%	[12% - 17%]	0%	[0% - 0%]
Medicaid	10%	[7% - 12%]	8%	[5% - 10%]
Medicare	17%	[15% - 18%]	29%	[26% - 32%]
Medicare + Medicaid dual	11%	[9% - 13%]	15%	[12% - 17%]
Non-reimbursable	26%	[26% - 26%]	0%	[0% - 0%]
Private (directly-purchased)	2%	[2% - 3%]	7%	[4% - 9%]
Private (employer-sponsored)	14%	[11% - 17%]	39%	[32% - 44%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 1%]	1%	[0% - 2%]
Unknown	2%	[2% - 2%]	0%	[0% - 0%]

Table 61: Ambulance requirements

Requirement	Count
Locations	3
Peak demand	6
Off-peak demand	4

Table 62: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$26
Est. labor cost	$2,241,327
Est. total cost	$3,586,123
Est. revenue potential	$2,643,721
Est. required subsidy	$942,402

8.6.13 Glendo Volunteer Ambulance Service

Table 63: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	55	0	54	1	110
2023	32	3	54	0	89
2024	29	0	31	1	61

Table 64: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 2%]	0%	[0% - 0%]
Medicaid	5%	[2% - 15%]	5%	[1% - 16%]
Medicare	22%	[15% - 27%]	40%	[28% - 56%]
Medicare + Medicaid dual	3%	[0% - 10%]	5%	[0% - 15%]
Non-reimbursable	49%	[49% - 49%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[0% - 8%]	8%	[0% - 25%]
Private (employer-sponsored)	14%	[5% - 22%]	41%	[22% - 61%]
TRICARE or VA	1%	[0% - 3%]	1%	[0% - 5%]
Uninsured (< 200% FPL)	0%	[0% - 3%]	0%	[0% - 2%]
Uninsured (>= 200% FPL)	0%	[0% - 2%]	1%	[0% - 3%]
Unknown	2%	[2% - 2%]	0%	[0% - 0%]

Table 65: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 66: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$16
Est. labor cost	$287,866
Est. total cost	$460,586
Est. revenue potential	$20,676
Est. required subsidy	$439,909

8.6.14 Hawk Springs-FD

Table 67: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	24	1	32	4	61
2023	17	1	26	0	44
2024	27	0	14	1	42

Table 68: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 3%]	0%	[0% - 0%]
Medicaid	11%	[3% - 22%]	6%	[1% - 14%]
Medicare	25%	[11% - 33%]	31%	[15% - 48%]
Medicare + Medicaid dual	10%	[0% - 19%]	10%	[0% - 20%]
Non-reimbursable	22%	[22% - 22%]	0%	[0% - 0%]
Private (directly-purchased)	11%	[3% - 19%]	21%	[0% - 38%]
Private (employer-sponsored)	15%	[0% - 22%]	29%	[0% - 42%]
TRICARE or VA	1%	[0% - 6%]	1%	[0% - 5%]
Uninsured (< 200% FPL)	2%	[0% - 8%]	1%	[0% - 3%]
Uninsured (>= 200% FPL)	1%	[0% - 6%]	2%	[0% - 7%]
Unknown	3%	[3% - 3%]	0%	[0% - 0%]

Table 69: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 70: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$15
Est. labor cost	$267,177
Est. total cost	$427,483
Est. revenue potential	$19,349
Est. required subsidy	$408,133

8.6.15 Hot Springs County - Mortimore Ambulance

Table 71: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	304	127	1	3	435
2023	307	138	2	2	449
2024	333	138	3	0	474

Table 72: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	9%	[6% - 14%]	4%	[3% - 7%]
Medicare	42%	[32% - 50%]	43%	[34% - 51%]
Medicare + Medicaid dual	27%	[19% - 36%]	21%	[14% - 32%]
Non-reimbursable	1%	[1% - 1%]	0%	[0% - 0%]
Private (directly-purchased)	7%	[1% - 12%]	11%	[1% - 20%]
Private (employer-sponsored)	12%	[5% - 18%]	19%	[9% - 29%]
TRICARE or VA	0%	[0% - 3%]	0%	[0% - 3%]
Uninsured (< 200% FPL)	2%	[0% - 4%]	1%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 4%]	1%	[0% - 3%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 73: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	2
Off-peak demand	2

Table 74: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$25
Est. labor cost	$867,938
Est. total cost	$1,388,701
Est. revenue potential	$306,947
Est. required subsidy	$1,081,754

8.6.16 Hulett EMS

Table 75: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	68	3	51	2	124
2023	52	1	36	0	89
2024	63	1	21	0	85

Table 76: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	4%	[0% - 7%]	2%	[1% - 5%]
Medicare	30%	[19% - 40%]	35%	[20% - 46%]
Medicare + Medicaid dual	13%	[4% - 27%]	12%	[0% - 24%]
Non-reimbursable	25%	[25% - 25%]	0%	[0% - 0%]
Private (directly-purchased)	6%	[1% - 13%]	12%	[3% - 24%]
Private (employer-sponsored)	19%	[12% - 25%]	37%	[25% - 48%]
TRICARE or VA	1%	[0% - 2%]	1%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 3%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 77: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 78: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$20
Est. labor cost	$357,564
Est. total cost	$572,102
Est. revenue potential	$47,706
Est. required subsidy	$524,397

8.6.17 Jackson Hole Fire/EMS

Table 79: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	774	182	590	29	1,575
2023	852	128	636	24	1,640
2024	846	50	585	8	1,489

Table 80: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	4%	[2% - 5%]	2%	[1% - 3%]
Medicare	23%	[22% - 25%]	31%	[28% - 33%]
Medicare + Medicaid dual	2%	[1% - 3%]	2%	[1% - 3%]
Non-reimbursable	39%	[39% - 39%]	0%	[0% - 0%]
Private (directly-purchased)	9%	[7% - 12%]	21%	[15% - 25%]
Private (employer-sponsored)	19%	[17% - 22%]	42%	[37% - 49%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[1% - 2%]	1%	[1% - 2%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 81: Ambulance requirements

Requirement	Count
Locations	7
Peak demand	2
Off-peak demand	1

Table 82: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$55
Est. labor cost	$1,433,672
Est. total cost	$2,293,875
Est. revenue potential	$734,717
Est. required subsidy	$1,559,157

8.6.18 Johnson County - Buffalo

Table 83: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	381	172	255	1	809
2023	376	207	229	10	822
2024	383	198	209	12	802

Table 84: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	3%	[1% - 5%]	2%	[1% - 3%]
Medicare	39%	[32% - 44%]	49%	[44% - 57%]
Medicare + Medicaid dual	11%	[6% - 15%]	10%	[6% - 16%]
Non-reimbursable	26%	[26% - 26%]	0%	[0% - 0%]
Private (directly-purchased)	6%	[4% - 10%]	12%	[7% - 21%]
Private (employer-sponsored)	11%	[8% - 14%]	24%	[18% - 31%]
TRICARE or VA	0%	[0% - 0%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 3%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 85: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	3
Off-peak demand	1

Table 86: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$27
Est. labor cost	$935,718
Est. total cost	$1,497,148
Est. revenue potential	$424,274
Est. required subsidy	$1,072,874

8.6.19 Johnson County - Kaycee

Table 87: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	62	3	64	0	129
2023	45	3	65	1	114
2024	42	3	55	0	100

Table 88: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	3%	[1% - 6%]	3%	[1% - 6%]
Medicare	26%	[21% - 30%]	54%	[41% - 67%]
Medicare + Medicaid dual	4%	[0% - 9%]	7%	[0% - 16%]
Non-reimbursable	55%	[55% - 55%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[0% - 8%]	13%	[3% - 28%]
Private (employer-sponsored)	7%	[3% - 12%]	22%	[9% - 36%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 2%]
Uninsured (< 200% FPL)	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 4%]	2%	[0% - 7%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 89: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 90: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$16
Est. labor cost	$281,783
Est. total cost	$450,853
Est. revenue potential	$31,951
Est. required subsidy	$418,902

8.6.20 LaGrange Fire Rescue

Table 91: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	27	0	19	0	46
2023	25	0	16	2	43
2024	27	0	20	0	47

Table 92: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	8%	[0% - 15%]	7%	[0% - 14%]
Medicare	21%	[9% - 30%]	34%	[15% - 56%]
Medicare + Medicaid dual	10%	[2% - 20%]	13%	[2% - 23%]
Non-reimbursable	41%	[41% - 41%]	0%	[0% - 0%]
Private (directly-purchased)	7%	[0% - 13%]	18%	[0% - 34%]
Private (employer-sponsored)	10%	[2% - 22%]	27%	[7% - 53%]
TRICARE or VA	1%	[0% - 4%]	1%	[0% - 5%]
Uninsured (< 200% FPL)	1%	[0% - 7%]	1%	[0% - 3%]
Uninsured (>= 200% FPL)	1%	[0% - 4%]	1%	[0% - 6%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 93: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 94: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$15
Est. labor cost	$268,589
Est. total cost	$429,743
Est. revenue potential	$16,519
Est. required subsidy	$413,224

8.6.21 Laramie Fire Department

Table 95: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	1,647	882	1,449	62	4,040
2023	1,760	829	1,485	51	4,125
2024	1,777	679	1,358	22	3,836

Table 96: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[3% - 7%]	3%	[2% - 4%]
Medicare	27%	[23% - 30%]	36%	[32% - 41%]
Medicare + Medicaid dual	8%	[4% - 10%]	8%	[4% - 11%]
Non-reimbursable	35%	[35% - 35%]	0%	[0% - 0%]
Private (directly-purchased)	6%	[4% - 9%]	14%	[9% - 20%]
Private (employer-sponsored)	17%	[14% - 20%]	38%	[32% - 44%]
TRICARE or VA	1%	[0% - 2%]	1%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 1%]	1%	[0% - 1%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 97: Ambulance requirements

Requirement	Count
Locations	3
Peak demand	5
Off-peak demand	3

Table 98: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$32
Est. labor cost	$2,209,728
Est. total cost	$3,535,564
Est. revenue potential	$1,928,788
Est. required subsidy	$1,606,777

8.6.22 Lingle Fire Department

Table 99: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	38	0	16	0	54
2023	41	1	20	0	62
2024	51	1	39	0	91

Table 100: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[1% - 8%]	3%	[1% - 6%]
Medicare	29%	[23% - 33%]	47%	[37% - 57%]
Medicare + Medicaid dual	8%	[3% - 15%]	11%	[4% - 20%]
Non-reimbursable	43%	[43% - 43%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[0% - 7%]	8%	[0% - 18%]
Private (employer-sponsored)	11%	[4% - 15%]	29%	[12% - 38%]
TRICARE or VA	0%	[0% - 3%]	1%	[0% - 4%]
Uninsured (< 200% FPL)	1%	[0% - 3%]	0%	[0% - 2%]
Uninsured (>= 200% FPL)	0%	[0% - 2%]	1%	[0% - 3%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 101: Ambulance requirements

Requirement	Count
Locations	2
Peak demand	1
Off-peak demand	1

Table 102: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$12
Est. labor cost	$201,547
Est. total cost	$322,475
Est. revenue potential	$32,171
Est. required subsidy	$290,304

8.6.23 Little Snake River

Table 103: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	37	1	37	0	75
2023	25	2	27	0	54
2024	43	0	32	0	75

Table 104: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 2%]	0%	[0% - 0%]
Medicaid	4%	[0% - 11%]	2%	[0% - 8%]
Medicare	31%	[22% - 38%]	41%	[28% - 54%]
Medicare + Medicaid dual	7%	[0% - 20%]	7%	[0% - 24%]
Non-reimbursable	33%	[33% - 33%]	0%	[0% - 0%]
Private (directly-purchased)	6%	[0% - 17%]	12%	[0% - 39%]
Private (employer-sponsored)	16%	[6% - 25%]	35%	[14% - 51%]
TRICARE or VA	0%	[0% - 3%]	0%	[0% - 4%]
Uninsured (< 200% FPL)	1%	[0% - 8%]	1%	[0% - 3%]
Uninsured (>= 200% FPL)	1%	[0% - 3%]	1%	[0% - 4%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 105: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 106: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$15
Est. labor cost	$270,514
Est. total cost	$432,823
Est. revenue potential	$31,877
Est. required subsidy	$400,946

8.6.24 Lusk EMS

Table 107: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	131	6	113	6	256
2023	133	19	92	2	246
2024	198	32	137	2	369

Table 108: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 3%]	0%	[0% - 0%]
Medicaid	12%	[7% - 18%]	9%	[5% - 15%]
Medicare	21%	[14% - 26%]	33%	[25% - 45%]
Medicare + Medicaid dual	8%	[2% - 14%]	10%	[2% - 18%]
Non-reimbursable	37%	[37% - 37%]	0%	[0% - 0%]
Private (directly-purchased)	7%	[2% - 14%]	18%	[5% - 34%]
Private (employer-sponsored)	10%	[6% - 15%]	26%	[16% - 39%]
TRICARE or VA	0%	[0% - 2%]	1%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	2%	[0% - 7%]	3%	[0% - 10%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 109: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	2
Off-peak demand	1

Table 110: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$12
Est. labor cost	$325,219
Est. total cost	$520,350
Est. revenue potential	$138,915
Est. required subsidy	$381,435

8.6.25 Memorial Hospital of Converse County

Table 111: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	843	303	1,543	20	2,709
2023	976	237	1,551	30	2,794
2024	1,014	265	1,368	25	2,672

Table 112: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	3%	[2% - 5%]	3%	[1% - 4%]
Medicare	21%	[19% - 23%]	37%	[32% - 40%]
Medicare + Medicaid dual	5%	[3% - 8%]	8%	[4% - 12%]
Non-reimbursable	51%	[51% - 51%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[2% - 6%]	10%	[5% - 18%]
Private (employer-sponsored)	14%	[10% - 16%]	41%	[32% - 47%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 1%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 1%]	1%	[0% - 1%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 113: Ambulance requirements

Requirement	Count
Locations	2
Peak demand	4
Off-peak demand	2

Table 114: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$29
Est. labor cost	$1,526,621
Est. total cost	$2,442,594
Est. revenue potential	$995,001
Est. required subsidy	$1,447,593

8.6.26 Mills Fire Department

Table 115: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	393	59	103	5	560
2023	432	25	107	3	567
2024	408	32	105	3	548

Table 116: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	10%	[6% - 14%]	6%	[3% - 8%]
Medicare	29%	[25% - 32%]	35%	[29% - 39%]
Medicare + Medicaid dual	15%	[8% - 19%]	13%	[6% - 18%]
Non-reimbursable	19%	[19% - 19%]	0%	[0% - 0%]
Private (directly-purchased)	6%	[2% - 10%]	12%	[5% - 19%]
Private (employer-sponsored)	17%	[13% - 23%]	32%	[24% - 43%]
TRICARE or VA	1%	[0% - 3%]	1%	[0% - 3%]
Uninsured (< 200% FPL)	1%	[0% - 3%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 3%]	1%	[0% - 3%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 117: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	2
Off-peak demand	1

Table 118: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$31
Est. labor cost	$803,281
Est. total cost	$1,285,250
Est. revenue potential	$307,674
Est. required subsidy	$977,576

8.6.27 Moorcroft Ambulance

Table 119: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	51	0	28	0	79
2023	48	0	47	0	95
2024	44	1	63	0	108

Table 120: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[0% - 8%]	4%	[0% - 8%]
Medicare	13%	[10% - 15%]	24%	[18% - 28%]
Medicare + Medicaid dual	2%	[0% - 4%]	2%	[0% - 6%]
Non-reimbursable	58%	[58% - 58%]	0%	[0% - 0%]
Private (directly-purchased)	2%	[0% - 6%]	6%	[0% - 17%]
Private (employer-sponsored)	20%	[15% - 25%]	62%	[48% - 73%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 2%]
Uninsured (< 200% FPL)	0%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 4%]	1%	[0% - 5%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 121: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 122: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$33
Est. labor cost	$569,690
Est. total cost	$911,504
Est. revenue potential	$35,822
Est. required subsidy	$875,681

8.6.28 North Big Horn Hospital Ambulance

Table 123: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	229	115	145	8	497
2023	230	121	154	9	514
2024	185	97	127	2	411

Table 124: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	5%	[2% - 9%]	3%	[2% - 6%]
Medicare	30%	[23% - 36%]	41%	[31% - 48%]
Medicare + Medicaid dual	14%	[8% - 22%]	15%	[8% - 24%]
Non-reimbursable	31%	[31% - 31%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[2% - 6%]	7%	[3% - 14%]
Private (employer-sponsored)	13%	[9% - 16%]	31%	[20% - 36%]
TRICARE or VA	0%	[0% - 2%]	0%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 2%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 125: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	2
Off-peak demand	1

Table 126: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$28
Est. labor cost	$737,008
Est. total cost	$1,179,212
Est. revenue potential	$205,100
Est. required subsidy	$974,112

8.6.29 Pine Bluffs EMS

Table 127: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	106	4	85	0	195
2023	102	4	63	0	169
2024	72	0	59	0	131

Table 128: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	3%	[0% - 7%]	3%	[0% - 6%]
Medicare	26%	[17% - 34%]	39%	[25% - 52%]
Medicare + Medicaid dual	10%	[2% - 20%]	11%	[1% - 23%]
Non-reimbursable	40%	[40% - 40%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[0% - 7%]	9%	[0% - 16%]
Private (employer-sponsored)	15%	[10% - 20%]	36%	[25% - 46%]
TRICARE or VA	0%	[0% - 2%]	1%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 3%]	0%	[0% - 2%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 3%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 129: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 130: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$17
Est. labor cost	$294,485
Est. total cost	$471,176
Est. revenue potential	$53,246
Est. required subsidy	$417,930

8.6.30 Powell Hospital Ambulance Service

Table 131: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	577	229	636	11	1,453
2023	483	216	540	7	1,246
2024	630	245	608	8	1,491

Table 132: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	3%	[2% - 5%]	3%	[1% - 4%]
Medicare	29%	[25% - 33%]	45%	[39% - 52%]
Medicare + Medicaid dual	10%	[6% - 15%]	13%	[7% - 18%]
Non-reimbursable	41%	[41% - 41%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[3% - 7%]	12%	[7% - 17%]
Private (employer-sponsored)	10%	[8% - 12%]	26%	[22% - 33%]
TRICARE or VA	0%	[0% - 0%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 2%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 133: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	3
Off-peak demand	2

Table 134: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$28
Est. labor cost	$1,226,142
Est. total cost	$1,961,827
Est. revenue potential	$636,240
Est. required subsidy	$1,325,587

8.6.31 Rawlins Fire Department

Table 135: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	4	4	13	0	21
2023	8	9	6	0	23
2024	6	13	10	0	29

Table 136: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	1%	[0% - 3%]	0%	[0% - 0%]
Medicaid	9%	[3% - 14%]	6%	[2% - 10%]
Medicare	16%	[10% - 21%]	22%	[12% - 32%]
Medicare + Medicaid dual	7%	[0% - 14%]	8%	[0% - 19%]
Non-reimbursable	34%	[34% - 34%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[0% - 10%]	7%	[0% - 25%]
Private (employer-sponsored)	26%	[14% - 38%]	56%	[38% - 72%]
TRICARE or VA	1%	[0% - 3%]	1%	[0% - 4%]
Uninsured (< 200% FPL)	2%	[0% - 7%]	1%	[0% - 3%]
Uninsured (>= 200% FPL)	1%	[0% - 3%]	1%	[0% - 3%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 137: Ambulance requirements

Requirement	Count
Locations	2
Peak demand	1
Off-peak demand	1

Table 138: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$30
Est. labor cost	$524,247
Est. total cost	$838,795
Est. revenue potential	$14,915
Est. required subsidy	$823,880

8.6.32 Salt Creek Emergency Services

Table 139: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	16	0	39	0	55
2023	18	0	51	1	70
2024	6	0	24	0	30

Table 140: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 4%]	0%	[0% - 0%]
Medicaid	1%	[0% - 4%]	3%	[0% - 10%]
Medicare	8%	[4% - 14%]	34%	[13% - 62%]
Medicare + Medicaid dual	5%	[0% - 11%]	18%	[0% - 47%]
Non-reimbursable	79%	[79% - 79%]	0%	[0% - 0%]
Private (directly-purchased)	1%	[0% - 4%]	5%	[0% - 24%]
Private (employer-sponsored)	5%	[4% - 11%]	37%	[23% - 64%]
TRICARE or VA	0%	[0% - 0%]	0%	[0% - 0%]
Uninsured (< 200% FPL)	0%	[0% - 4%]	1%	[0% - 6%]
Uninsured (>= 200% FPL)	0%	[0% - 4%]	2%	[0% - 13%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 141: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 142: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$10
Est. labor cost	$168,736
Est. total cost	$269,978
Est. revenue potential	$3,724
Est. required subsidy	$266,254

8.6.33 Sheridan Fire-Rescue

Table 143: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	14	1	536	0	551
2023	10	0	629	3	642
2024	2	0	753	11	766

Table 144: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	0%	[0% - 0%]	0%	[0% - 0%]
Medicare	0%	[0% - 0%]	77%	[50% - 100%]
Medicare + Medicaid dual	0%	[0% - 0%]	23%	[0% - 50%]
Non-reimbursable	98%	[98% - 98%]	0%	[0% - 0%]
Private (directly-purchased)	0%	[0% - 0%]	0%	[0% - 0%]
Private (employer-sponsored)	0%	[0% - 0%]	0%	[0% - 0%]
TRICARE or VA	0%	[0% - 0%]	0%	[0% - 0%]
Uninsured (< 200% FPL)	0%	[0% - 0%]	0%	[0% - 0%]
Uninsured (>= 200% FPL)	0%	[0% - 0%]	0%	[0% - 0%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 145: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 146: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$32
Est. labor cost	$563,706
Est. total cost	$901,930
Est. revenue potential	$1,222
Est. required subsidy	$900,708

8.6.34 South Central WY Emergency Medical Services

Table 147: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	337	9	342	25	713
2023	268	18	326	38	650
2024	260	87	240	17	604

Table 148: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	4%	[2% - 5%]	3%	[1% - 4%]
Medicare	25%	[22% - 29%]	38%	[32% - 44%]
Medicare + Medicaid dual	5%	[1% - 8%]	6%	[1% - 10%]
Non-reimbursable	40%	[40% - 40%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[1% - 5%]	7%	[2% - 14%]
Private (employer-sponsored)	18%	[15% - 22%]	44%	[37% - 50%]
TRICARE or VA	0%	[0% - 2%]	1%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	1%	[0% - 2%]
Unknown	3%	[3% - 3%]	0%	[0% - 0%]

Table 149: Ambulance requirements

Requirement	Count
Locations	5
Peak demand	2
Off-peak demand	1

Table 150: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$14
Est. labor cost	$355,234
Est. total cost	$568,375
Est. revenue potential	$272,722
Est. required subsidy	$295,653

8.6.35 South Lincoln EMS

Table 151: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	134	86	193	30	443
2023	178	79	256	10	523
2024	180	54	214	2	450

Table 152: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	3%	[0% - 5%]	2%	[0% - 5%]
Medicare	26%	[23% - 28%]	43%	[37% - 48%]
Medicare + Medicaid dual	4%	[1% - 6%]	5%	[1% - 8%]
Non-reimbursable	48%	[48% - 48%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[1% - 6%]	7%	[2% - 15%]
Private (employer-sponsored)	15%	[10% - 18%]	41%	[31% - 50%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 2%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 4%]	2%	[0% - 5%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 153: Ambulance requirements

Requirement	Count
Locations	3
Peak demand	2
Off-peak demand	1

Table 154: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$25
Est. labor cost	$666,569
Est. total cost	$1,066,511
Est. revenue potential	$181,498
Est. required subsidy	$885,013

8.6.36 Star Valley Health EMS

Table 155: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	370	165	331	19	885
2023	518	195	218	27	958
2024	494	226	220	13	953

Table 156: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[3% - 6%]	2%	[2% - 3%]
Medicare	34%	[30% - 37%]	39%	[35% - 42%]
Medicare + Medicaid dual	8%	[3% - 12%]	7%	[3% - 11%]
Non-reimbursable	23%	[23% - 23%]	0%	[0% - 0%]
Private (directly-purchased)	8%	[6% - 11%]	14%	[11% - 20%]
Private (employer-sponsored)	19%	[16% - 21%]	35%	[31% - 41%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 3%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	2%	[0% - 3%]	1%	[0% - 2%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 157: Ambulance requirements

Requirement	Count
Locations	3
Peak demand	3
Off-peak demand	2

Table 158: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$32
Est. labor cost	$1,421,464
Est. total cost	$2,274,342
Est. revenue potential	$566,440
Est. required subsidy	$1,707,902

8.6.37 Sublette County EMS

Table 159: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	340	312	1,030	13	1,695
2023	390	282	950	12	1,634
2024	386	340	1,161	11	1,898

Table 160: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	1%	[1% - 2%]	1%	[1% - 2%]
Medicare	21%	[19% - 23%]	47%	[44% - 51%]
Medicare + Medicaid dual	2%	[0% - 4%]	3%	[0% - 7%]
Non-reimbursable	61%	[61% - 61%]	0%	[0% - 0%]
Private (directly-purchased)	3%	[2% - 4%]	11%	[6% - 16%]
Private (employer-sponsored)	10%	[8% - 11%]	36%	[31% - 42%]
TRICARE or VA	0%	[0% - 0%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 1%]	1%	[0% - 2%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 161: Ambulance requirements

Requirement	Count
Locations	3
Peak demand	4
Off-peak demand	2

Table 162: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$27
Est. labor cost	$1,417,509
Est. total cost	$2,268,014
Est. revenue potential	$594,114
Est. required subsidy	$1,673,900

8.6.38 Ten Sleep Ambulance Service

Table 163: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	38	0	54	0	92
2023	46	0	58	0	104
2024	47	2	50	0	99

Table 164: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 2%]	0%	[0% - 0%]
Medicaid	5%	[0% - 10%]	4%	[0% - 10%]
Medicare	21%	[11% - 30%]	38%	[17% - 55%]
Medicare + Medicaid dual	5%	[0% - 14%]	7%	[0% - 20%]
Non-reimbursable	51%	[51% - 51%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[1% - 11%]	13%	[3% - 34%]
Private (employer-sponsored)	11%	[4% - 17%]	33%	[11% - 51%]
TRICARE or VA	1%	[0% - 3%]	1%	[0% - 4%]
Uninsured (< 200% FPL)	1%	[0% - 3%]	1%	[0% - 2%]
Uninsured (>= 200% FPL)	2%	[0% - 6%]	3%	[0% - 11%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 165: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 166: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$16
Est. labor cost	$272,250
Est. total cost	$435,601
Est. revenue potential	$33,621
Est. required subsidy	$401,980

8.6.39 Torrington Emergency Medical Services

Table 167: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	609	200	510	18	1,337
2023	642	212	489	8	1,351
2024	665	228	385	4	1,282

Table 168: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[3% - 6%]	2%	[2% - 4%]
Medicare	35%	[30% - 41%]	48%	[41% - 54%]
Medicare + Medicaid dual	15%	[8% - 20%]	16%	[9% - 22%]
Non-reimbursable	30%	[30% - 30%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[2% - 6%]	8%	[4% - 14%]
Private (employer-sponsored)	11%	[9% - 14%]	24%	[19% - 30%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 1%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	0%	[0% - 1%]	0%	[0% - 1%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 169: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	3
Off-peak demand	2

Table 170: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$21
Est. labor cost	$908,856
Est. total cost	$1,454,169
Est. revenue potential	$635,969
Est. required subsidy	$818,201

8.6.40 Town of Pine Haven - EMS

Table 171: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	6	0	0	0	6
2023	0	0	1	0	1
2024	17	0	1	0	18

Table 172: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	4%	[0% - 11%]	2%	[0% - 6%]
Medicare	55%	[33% - 72%]	53%	[34% - 76%]
Medicare + Medicaid dual	13%	[0% - 33%]	10%	[0% - 28%]
Non-reimbursable	6%	[6% - 6%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[0% - 17%]	6%	[0% - 25%]
Private (employer-sponsored)	18%	[11% - 22%]	28%	[17% - 37%]
TRICARE or VA	0%	[0% - 0%]	0%	[0% - 0%]
Uninsured (< 200% FPL)	0%	[0% - 0%]	0%	[0% - 0%]
Uninsured (>= 200% FPL)	1%	[0% - 6%]	1%	[0% - 5%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 173: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 174: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$13
Est. labor cost	$234,581
Est. total cost	$375,330
Est. revenue potential	$10,724
Est. required subsidy	$364,606

8.6.41 Uinta County Fire/EMS

Table 175: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	1,040	284	606	31	1,961
2023	1,021	323	624	91	2,059
2024	1,078	294	604	68	2,044

Table 176: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	10%	[8% - 12%]	6%	[5% - 8%]
Medicare	25%	[23% - 27%]	35%	[31% - 39%]
Medicare + Medicaid dual	9%	[7% - 12%]	10%	[7% - 13%]
Non-reimbursable	30%	[30% - 30%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[2% - 5%]	8%	[5% - 12%]
Private (employer-sponsored)	17%	[14% - 20%]	38%	[33% - 44%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[1% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[0% - 2%]	2%	[0% - 3%]
Unknown	3%	[3% - 3%]	0%	[0% - 0%]

Table 177: Ambulance requirements

Requirement	Count
Locations	7
Peak demand	4
Off-peak demand	2

Table 178: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$29
Est. labor cost	$1,543,394
Est. total cost	$2,469,431
Est. revenue potential	$982,454
Est. required subsidy	$1,486,977

8.6.42 Upton-FD

Table 179: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	10	3	15	0	28
2023	5	1	11	0	17
2024	10	0	23	0	33

Table 180: Estimated payer mix

	Volume		Revenue	
Payer	**Percent**	**Range**	**Percent**	**Range**
Indian Health Services	0%	[0% - 0%]	0%	[0% - 0%]
Medicaid	3%	[0% - 6%]	4%	[0% - 11%]
Medicare	15%	[9% - 18%]	46%	[27% - 65%]
Medicare + Medicaid dual	4%	[0% - 9%]	10%	[0% - 24%]
Non-reimbursable	70%	[70% - 70%]	0%	[0% - 0%]
Private (directly-purchased)	1%	[0% - 3%]	7%	[0% - 19%]
Private (employer-sponsored)	6%	[3% - 12%]	31%	[15% - 53%]
TRICARE or VA	0%	[0% - 0%]	0%	[0% - 0%]
Uninsured (< 200% FPL)	0%	[0% - 3%]	0%	[0% - 3%]
Uninsured (>= 200% FPL)	1%	[0% - 3%]	2%	[0% - 10%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 181: Ambulance requirements

Requirement	Count
Locations	2
Peak demand	1
Off-peak demand	1

Table 182: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$16
Est. labor cost	$281,172
Est. total cost	$449,875
Est. revenue potential	$6,608
Est. required subsidy	$443,266

8.6.43 Wamsutter EMS

Table 183: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	31	0	68	1	100
2023	53	0	117	0	170
2024	36	0	82	1	119

Table 184: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	6%	[1% - 12%]	7%	[1% - 16%]
Medicare	1%	[0% - 3%]	3%	[0% - 9%]
Medicare + Medicaid dual	1%	[0% - 4%]	3%	[0% - 8%]
Non-reimbursable	69%	[69% - 69%]	0%	[0% - 0%]
Private (directly-purchased)	2%	[0% - 5%]	7%	[0% - 20%]
Private (employer-sponsored)	18%	[12% - 23%]	76%	[56% - 92%]
TRICARE or VA	0%	[0% - 3%]	1%	[0% - 5%]
Uninsured (< 200% FPL)	1%	[0% - 4%]	1%	[0% - 3%]
Uninsured (>= 200% FPL)	1%	[0% - 3%]	2%	[0% - 6%]
Unknown	1%	[1% - 1%]	0%	[0% - 0%]

Table 185: Ambulance requirements

Requirement	Count
Locations	1
Peak demand	1
Off-peak demand	1

Table 186: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$24
Est. labor cost	$421,051
Est. total cost	$673,682
Est. revenue potential	$30,043
Est. required subsidy	$643,638

8.6.44 Wyoming Medical Center

Table 187: Volume by SFY and Response Type

SFY	911 Response	Transport	Non-reimbursable	Unknown	Total
2022	5,904	2,537	4,410	105	12,956
2023	6,083	2,529	4,290	112	13,014
2024	6,136	2,665	3,854	61	12,716

Table 188: Estimated payer mix

	Volume		Revenue	
Payer	Percent	Range	Percent	Range
Indian Health Services	0%	[0% - 1%]	0%	[0% - 0%]
Medicaid	8%	[6% - 9%]	5%	[4% - 6%]
Medicare	26%	[24% - 29%]	36%	[32% - 40%]
Medicare + Medicaid dual	13%	[11% - 15%]	14%	[11% - 17%]
Non-reimbursable	30%	[30% - 30%]	0%	[0% - 0%]
Private (directly-purchased)	4%	[3% - 5%]	8%	[6% - 11%]
Private (employer-sponsored)	16%	[14% - 18%]	35%	[32% - 39%]
TRICARE or VA	0%	[0% - 1%]	0%	[0% - 1%]
Uninsured (< 200% FPL)	1%	[0% - 2%]	0%	[0% - 1%]
Uninsured (>= 200% FPL)	1%	[1% - 2%]	1%	[1% - 2%]
Unknown	0%	[0% - 0%]	0%	[0% - 0%]

Table 189: Ambulance requirements

Requirement	Count
Locations	3
Peak demand	6
Off-peak demand	4

Table 190: Est. cost and revenue

Category	Value
Avg. hourly labor cost	$29
Est. labor cost	$2,547,915
Est. total cost	$4,076,663
Est. revenue potential	$6,364,433
Est. required subsidy	-$2,287,770

9 Technical Appendix

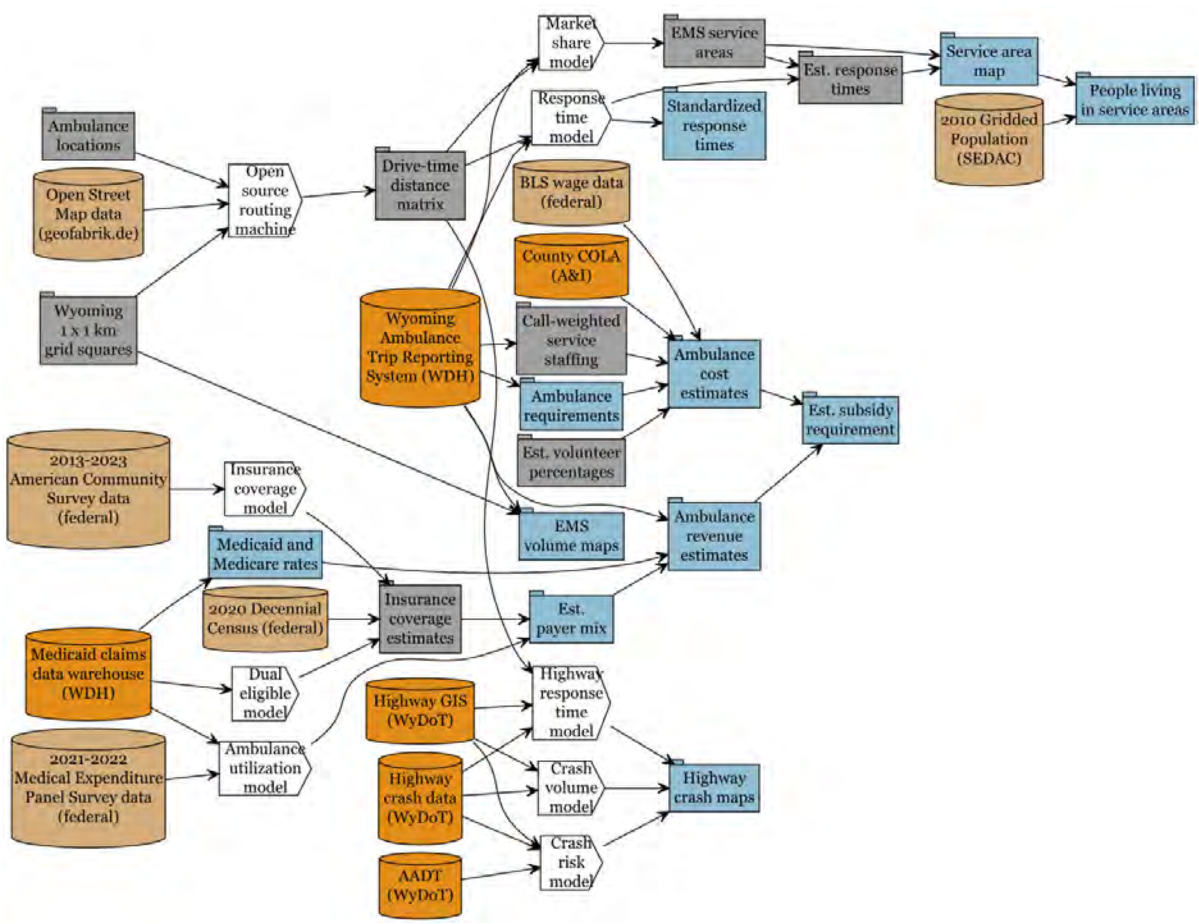
This section contains additional detail on how we developed our estimates. As noted in the report itself, it is intended to "show our work" in case people have questions about the statistical methodologies behind our estimates.

9.1 Data and model overview

Figure 15 outlines how the various 'final products' of this report —shown in light blue boxes —are derived from source data. On the figure:

- **Underlying data sources** are depicted as cylinders. State-owned data are colored in orange, and outside (e.g. federal or third-party) are shown in tan;
- **Statistical models** are shown as white boxed arrows; and,
- **Intermediate products** are shown as gray boxes.

Figure 15: Modeling framework



9.2 Service area models

When looking at geography, the trip report data we have is fairly sparse; as you can see in the geographic risk section, calls tend to concentrate in cities and towns, and there's not enough geographic coverage for us to estimate EMS service areas using the raw data alone.

This is where statistical models come in handy to extrapolate outcomes based on known variables, and thus fill in the gaps for the ~260,000 grid squares we're trying to map.

The purpose of this particular model is to estimate the probability that a certain EMS agency will respond to a call coming from *any given grid square* in the State of Wyoming, based on three knowable factors:

- The drive time from that grid square to the five (5) closest ambulance services;
- The capabilities (ambulance + staff) of each of those five potential services;
- The name of each of the five services, which embodies everything particular about the service, including capabilities, but also including unobserved factors.

9.2.1 Discrete choice logit model specifications

Because this probability represents a 'market share' of hypothetical calls, we rely on a **discrete choice logit model**, which can be used in marketing research to elicit consumer preferences.[57]

In this model, a 911 dispatcher receiving a call from location i faces a choice of dispatching one of the five closest services $j \in \{1, 2, 3, 4, 5\}$, where 1 is the closest and 5 is the furthest away.

If we define the 'economic utility' of the 911 dispatcher in terms of the best service to respond to that particular location (i.e., some combination of which ambulance is closest, and which service has the most capacity), it can be broken into what we *can* observe (V_{ij}) and some "random" component we can't observe (ϵ_{ij}). In the logit model, this random component is modeled using an independently and identically distributed Gumbel distribution.[58]

The two models we consider for the observable fixed utility V_{ij} are:

(1) $V_{ij} = \beta_0 \times \text{Drive time from service}_j \text{ to location}_i + \beta_1 \times \text{Capacity of service}_j$

where "capacity" of service j is measured as the sum of the service's ambulances and total licensed staff (divided by 5.44 to make the staff component roughly on the same scale as the number of ambulances), and;

(2) $V_{ij} = \beta_0 \times \text{Drive time from service}_j \text{ to location}_i + \beta_{\text{[Service]}} \times \text{Service name}_j$

This is a fixed effects model, where the 'capacity' of each service is considered more holistically, and includes un-measurable factors like medical capacity, reputation, etc.

[57] For example, predicting which of five candy bars will be chosen based on variables like price, milk/dark chocolate, percent cacao, etc. Actual choice models used are often much more complicated (e.g., incorporating characteristics of the people choosing the products), so the logit choice model is usually used as more of a learning tool.

[58] This distribution has the convenient property that each choice probability can be simplified to a softmax function: $P_{ij} = \frac{e^{V_{ij}}}{\sum_j e^{V_{ij}}}$. The downsides of the logit model are: (1) it assumes that the fixed utility calculation is the same for all locations i, and (2) it assumes the "random" utility component is also the same (i.i.d. Gumbel). We do not believe either assumption is a problem for the purpose of this model; there is no reason, for example, to believe that dispatchers in one area value certain EMS agency attributes differently from dispatchers in another area.

We use the mlogit package[59] to estimate each model using maximum likelihood techniques, as the model dataset is very large (299,395 rows resulting from 5 ×59,879 911 calls).

9.2.2 Data processing

Significant data processing is required to get the 911 call data into the right format; we need to know not only which service responded to each call, but also the likely service options the 911 dispatcher may have considered.

- We first generated a drive time matrix between all 267,270 grid squares in the State and the 20 closest ambulance services, relying heavily on a local Open Source Routing Machine[60] engine and Wyoming Open Street Map data to process ~ 5.3M drive time calculations.[61]
- From this matrix, we identified the closest five services (i.e., services often have multiple ambulance locations, so we took the minimum distance for each service), ranked in order of drive time.
- By joining the coordinates for each 911 response in the WATRS data to kilometer grid squares, we merged in the potential choice information based on location.
- After standardizing drive times and calculating capacity for each of the five closest agencies, the choice set *for each 911 call* looks like the example in Table 191.

In this one example, the call came from grid square 5651, between Etna and Alpine in the the Star Valley. The five closest agencies to that square are shown with their capabilities and drive times to that square. In this case, Star Valley Health was ultimately dispatched.

Table 191: Choice set for one 911 call

Agency	Staff	Ambulances	Drive time
Star Valley Health EMS	41	8	12.3
Jackson Hole Fire/EMS	66	6	46.7
Teton County Fire Protection District	32	5	92.6
Sublette County EMS	39	8	108.1
Frontier Ambulance	48	14	193.5

The results from each choice model follow:

9.2.3 Capacity model results

This is the simplest model, predicting choice based on drive time and capacity (ambulances and staff). Intuitively, the coefficients indicate that the lower the drive time and the higher the capacity, the more likely a particular service will be dispatched.

[59] Croissant Y (2020). "Estimation of Random Utility Models in R: The mlogit Package." Journal of Statistical Software, 95(11), 1–41. doi:10.18637/jss.v095.i11., https://cran.r-project.org/web/packages/mlogit/

[60] https://project-osrm.org/

[61] We did prune the initial list using "as the crow flies" haversine distance so as to not estimate drive times between a call in Gillette and an ambulance in Cheyenne, for example.

```
Call:
mlogit(formula = ChosenRank ~ zTime + Cap | 0, data = choice_model,
    method = "nr")

Frequencies of alternatives:choice
      Svc1       Svc2       Svc3       Svc4       Svc5
0.85948329 0.13022930 0.00764876 0.00205414 0.00058451

nr method
9 iterations, 0h:0m:5s
g'(-H)^-1g = 0.000157
successive function values within tolerance limits

Coefficients :
        Estimate Std. Error  z-value              Pr(>|z|)
zTime -5.8446562  0.0533697 -109.513 < 0.00000000000000022 ***
Cap    0.1191838  0.0012754   93.446 < 0.00000000000000022 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -12493
```

9.2.4 Fixed effects model results

This model is more complex, as it has coefficients for drive time, but also one for each agency. The drive time coefficient is in the same ballpark as the previous model. Larger coefficients (e.g. for the full-time services like AMR, WMC) indicate a service is more likely to be dispatched after adjusting for drive time.

```
Call:
mlogit(formula = ChosenRank ~ zTime + AgencyName | 0, data = choice_model,
    method = "nr")

Frequencies of alternatives:choice
      Svc1       Svc2       Svc3       Svc4       Svc5
0.85948329 0.13022930 0.00764876 0.00205414 0.00058451

nr method
10 iterations, 0h:0m:21s
g'(-H)^-1g = 0.000179
successive function values within tolerance limits

Coefficients :
                                                            Estimate Std. Error  z-value              Pr(>|z|)
zTime                                                      -6.469617   0.090274 -71.6667 < 0.00000000000000022 ***
AgencyNameAmerican Medical Response                         8.048564   0.447320  17.9929 < 0.00000000000000022 ***
AgencyNameBanner Health Paramedic Services - Platte County  7.099215   0.503095  14.1111 < 0.00000000000000022 ***
AgencyNameBHFD #4 Ambulance                                 0.153683   1.121273   0.1371             0.8909826
AgencyNameCampbell County Health EMS                        2.355095   0.915639   2.5721             0.0101090 *
AgencyNameCarbon County EMS                                 3.296168   0.797423   4.1335 0.0000357244799649159 ***
AgencyNameCastle Rock Hospital District-Emergency Services  2.925045   0.979342   2.9867             0.0028196 **
AgencyNameCody Regional Health EMS                          1.976563   1.065670   1.8548             0.0636305 .
AgencyNameCrook County Medical Services District EMS        0.471216   0.950079   0.4960             0.6199116
AgencyNameEden Farson Fire District                        -0.553478   0.994390  -0.5566             0.5778006
AgencyNameEvansville Emergency Services                     4.331673   0.581893   7.4441 0.0000000000000976996 ***
AgencyNameFrontier Ambulance                                5.622867   0.891960   6.3039 0.0000000002901634488 ***
AgencyNameGlendo Volunteer Ambulance Service                3.066359   0.535204   5.7293 0.0000000100829704586 ***
AgencyNameHawk Springs-FD                                   5.007981   0.533709   9.3834 < 0.00000000000000022 ***
AgencyNameHot Springs County - Mortimore Ambulance         -0.195733   1.062299  -0.1843             0.8538142
AgencyNameHulett EMS                                        1.157869   1.078896   1.0732             0.2831824
AgencyNameJackson Hole Fire/EMS                             2.074441   0.998614   2.0773             0.0377721 *
AgencyNameJohnson County - Buffalo                          0.406174   0.919965   0.4415             0.6588437
AgencyNameJohnson County - Kaycee                           0.401838   0.771161   0.5211             0.6023095
AgencyNameLaGrange Fire Rescue                              3.017087   0.552780   5.4580 0.0000000481460462609 ***
AgencyNameLaramie Fire Department                           7.011882   0.497558  14.0926 < 0.00000000000000022 ***
AgencyNameLingle Fire Department                            5.682599   0.537194  10.5783 < 0.00000000000000022 ***
AgencyNameLittle Snake River                                1.551942   1.948028   0.7967             0.4256407
```

```
AgencyNameLusk EMS                                          5.356879   0.658437   8.1357 0.0000000000000004441 ***
AgencyNameMemorial Hospital of Converse County              5.160732   0.571192   9.0350 < 0.00000000000000022 ***
AgencyNameMills Fire Department                             4.167255   0.581330   7.1685 0.0000000000007582823 ***
AgencyNameMoorcroft Ambulance                              -2.380380   0.928770  -2.5629             0.0103790 *
AgencyNameNorth Big Horn Hospital Ambulance                 1.403786   1.078073   1.3021             0.1928737
AgencyNamePine Bluffs EMS                                   2.397818   0.442595   5.4176 0.0000000603924630305 ***
AgencyNamePowell Hospital Ambulance Service                 1.666947   1.070927   1.5565             0.1195783
AgencyNameRawlins Fire Department                          -1.550343   0.851787  -1.8201             0.0687427 .
AgencyNameSalt Creek Emergency Services                    -2.117683   0.638065  -3.3189             0.0009037 ***
AgencyNameSheridan Fire-Rescue                              0.919989   0.916338   1.0040             0.3153863
AgencyNameSouth Central WY Emergency Medical Services       1.567639   0.618448   2.5348             0.0112514 *
AgencyNameSouth Lincoln EMS                                 3.155264   1.205014   2.6184             0.0088331 **
AgencyNameStar Valley Health EMS                            2.231230   1.120268   1.9917             0.0464047 *
AgencyNameSublette County EMS                               5.711393   0.994676   5.7420 0.0000000093585021954 ***
AgencyNameTen Sleep Ambulance Service                      -2.127990   1.090522  -1.9514             0.0510154 .
AgencyNameTeton County Fire Protection District             3.529607   1.005190   3.5114             0.0004458 ***
AgencyNameTorrington Emergency Medical Services             7.901149   0.536062  14.7393 < 0.00000000000000022 ***
AgencyNameTown of Pine Haven - EMS                         -4.167832   0.988620  -4.2158 0.0000248887355460692 ***
AgencyNameUinta County Fire/EMS                             0.639241   1.124497   0.5685             0.5697171
AgencyNameUpton-FD                                         -4.309319   0.945327  -4.5585 0.0000051508302914005 ***
AgencyNameWamsutter EMS                                     1.253406   0.808285   1.5507             0.1209740
AgencyNameWyoming Medical Center                            6.970730   0.579830  12.0220 < 0.00000000000000022 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Log-Likelihood: -8796.5
```

9.2.5 Model comparison and predictions

Comparing the two models using a likelihood ratio test (below), the more complex one (e.g. 45 degrees of freedom vs. 2) clearly fits the data better.

```
Likelihood ratio test

Model 1: ChosenRank ~ zTime + Cap | 0
Model 2: ChosenRank ~ zTime + AgencyName | 0
  #Df   LogLik Df  Chisq            Pr(>Chisq)
1   2 -12492.7
2  45  -8796.5 43 7392.5 < 0.00000000000000022 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

At this point, we predicted market shares using both models for every grid square in the State, and then blended the predictions together in a 20% - 80% weighted average, favoring the more complex fixed-effects model, but including some influence of the simpler explicit capability model.

9.3 Response time models

This section actually describes two models, which are combined to estimate overall response times:

- A "chute time" model, which tries to capture the important factors in how long it takes between the time a 911 call is received and the time the ambulance starts rolling; and,
- A "response time" model, which looks at how long it takes to arrive on scene.

9.3.1 Data sources

Unlike the service area models, we don't have to process the WATRS data too much here.

In addition to information on the patient and the agency responding, each 911 call has timestamps associated with events like:

- The call was received;
- The ambulance got moving;
- The ambulance arrived on scene;
- The patient arrived at his/her destination; and,
- The ambulance was back in service.

To this dataset, we add the calculated drive time (using the methods in the previous section) between the closest ambulance locations for the service that responded and the grid square of the call.

We then stratified the dataset by agency and selected up to 250 calls for each agency for modeling purposes.

9.3.2 Dispatch time

This Generalized Additive Model estimates the time between the call (i) being received and the time the ambulance gets moving as a function of: (1) the agency (j) responding (2) the hour of the day the call was received, and (3) the interaction between the two.

$$\text{Dispatch time}_{ij} \sim \text{Weibull}\left(\lambda_{ij}, \kappa\right)$$

Here, the scale parameter λ_{ij} is parameterized by the mean μ_{ij} and shape parameter κ, and μ_{ij} is modeled using a log link of a smooth tensor product of hour of the day (HoD), using a cyclic spline (e.g., so 0:00 and 24:00 mean the same thing) and agency, using a random effect, with smoothing parameters τ_1 and tau_2, respectively .

Essentially, this allows the "hour of the day effect" to be a "wiggly line" that varies by agency, in addition to the agency effect itself. This is important because larger services like AMR likely have less variation in their dispatch times between peak and off-peak hours compared with smaller volunteer services.

$$\begin{aligned} \lambda_{ij} &= \frac{\mu_{ij}}{\Gamma(1+\frac{1}{\kappa})} \\ \log(\mu_{ij}) &= \alpha + \text{t2}_{cc}^{re}(\text{Hour of the day}_i, \text{Agency}_j, \tau_1, \tau_2) \end{aligned}$$

Finally, we assign the following priors to each parameter, chosen to keep most probability mass within the likely space and thus aid in computation.

$$\begin{aligned}\alpha &\sim \mathcal{N}(1, 2)\\ \tau_1, \tau_2 &\sim \text{Student}(3, 0, 0.5)\\ \kappa &\sim \text{Gamma}(0.01, 0.01)\end{aligned}$$

The output from the model, using MCMC methods with Stan[62], the cmdstanr[63] interface and the brms[64] wrapper, is below:

```
 Family: weibull
  Links: mu = log; shape = identity
Formula: DispatchTime ~ 1 + t2(HoD, Agency, k = c(4, 40), bs = c("cc", "re"))
   Data: model_sample (Number of observations: 6303)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smoothing Spline Hyperparameters:
                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(t2HoDAgency_1)     0.37      0.04     0.31     0.45 1.01      569      738
sds(t2HoDAgency_2)     1.84      0.19     1.51     2.26 1.02      285      495

Regression Coefficients:
          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept     1.35      0.09     1.18     1.53 1.03       63       97

Further Distributional Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
shape     1.79      0.02     1.76     1.82 1.00     4115     1419

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
```

In addition to this diagnostic, a posterior predictive check of the overall outcome (dispatch time) indicates good fit with the data (see Figure 16). This plot also shows how dispatch times are generally distributed under 20 minutes.

9.3.3 Response time

This model is similar to the dispatch model, but it uses a likelihood with a longer tail (i.e., a lognormal) to model the drive time to call i by EMS service j, with an average μ_{ij} predicted by:

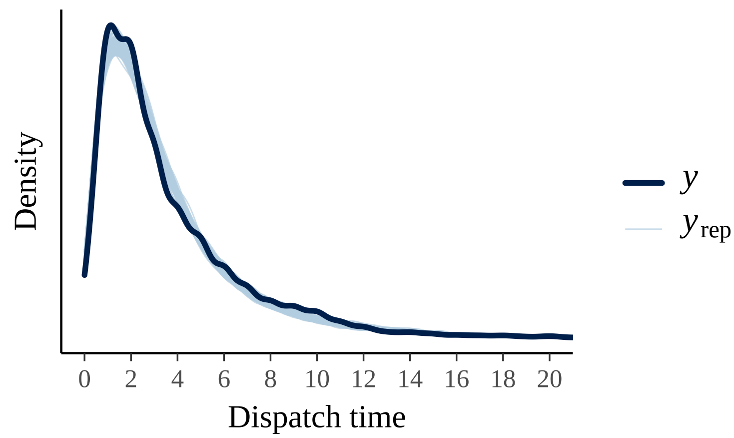
- The "Google maps" (actually Open Street Maps) drive time estimate from the closest ambulance to the incident, which is analogous to distance, but also factors in speed limits, road types, etc.;
- A smooth cyclic function of the month of the response (e.g., under the assumption that winter driving is slower than summer); and ,

[62] Stan Development Team. 2023. Stan Modeling Language Users Guide and Reference Manual, 2.32. https://mc-stan.org

[63] Gabry J, Češnovar R, Johnson A (2023). cmdstanr: R Interface to 'CmdStan'. https://mc-stan.org/cmdstanr/, https://discourse.mc-stan.org.

[64] Bürkner P (2017). "brms: An R Package for Bayesian Multilevel Models Using Stan." Journal of Statistical Software, 80(1), 1–28. doi:10.18637/jss.v080.i01.

Figure 16: Posterior predictive check, dispatch times



- A varying intercept for the EMS service j.

$$\text{Response time}_{ij} \sim \text{Lognormal}\left(\mu_{ij}, \sigma\right)$$
$$\mu_{ij} = \alpha + \beta \times \text{Calculated drive time}_{ij} + \mathrm{s}^{cc}(\text{Month of year}_{ij}, \tau) + \alpha_{[\text{Agency}]}$$

As with the previous model, we use regularizing priors for the probability space:

$$\begin{aligned}
\alpha &\sim \mathcal{N}(1,2) \\
\alpha_{[\text{Agency}]} &\sim \text{Student}(3,0,1) \\
\beta &\sim \text{Student}(3,0,1) \\
\tau &\sim \text{Student}(3,0,1) \\
\sigma &\sim \text{Student}(3,0,2.5)
\end{aligned}$$

The output of the model follows, as well as the posterior predictive check in Figure 17.

```
 Family: lognormal
  Links: mu = identity; sigma = identity
Formula: ResponseTime ~ 1 + minDur + s(Month, k = 4, bs = "cc") + (1 | Agency)
   Data: model_sample (Number of observations: 6303)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smoothing Spline Hyperparameters:
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(sMonth_1)     0.06      0.07     0.00     0.28 1.01      404      759

Multilevel Hyperparameters:
~Agency (Number of levels: 45)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.26      0.03     0.20     0.34 1.01      365      425

Regression Coefficients:
```

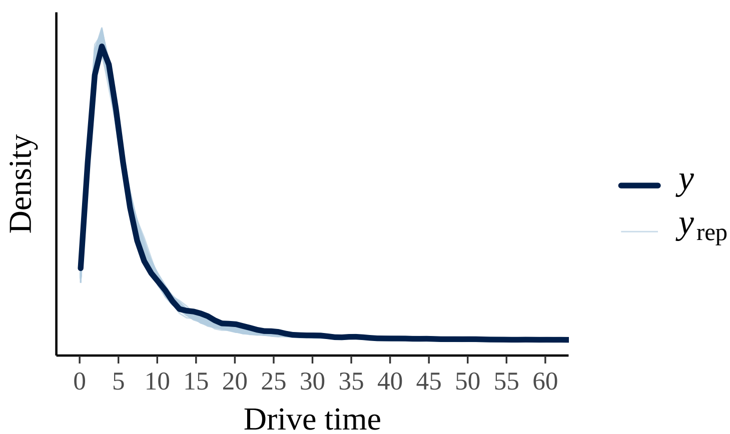
```
          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept     1.10      0.04     1.02     1.17 1.01      190      295
minDur        0.06      0.00     0.05     0.06 1.00     2249     1250

Further Distributional Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma     0.72      0.01     0.70     0.73 1.00     2218     1223

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).

Warning message:
There were 33 divergent transitions after warmup. Increasing adapt_delta above 0.8 may help.
See http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
```

Figure 17: Posterior predictive check, travel times



9.4 Payer mix and ambulance risk models

Since WATRS data has very little information about the payer of each EMS call, we also have to estimate this. As noted on 15, we use three model-based estimates to do so:

- First, we apply an **insurance coverage model** (derived from American Community Survey data, as described below) to the decennial 2020 Census. This gives us the probability that a given person from a demographic cell (e.g. 0-5 year old female Asian American / Pacific Islander) living in a certain census block group (there are 457 of these block groups in Wyoming) is covered by a certain payer (e.g., in this case, Employer Sponsored Insurance (ESI), directly-purchased private coverage, or Medicaid are most likely).

  Since we have better in-house data on dual-eligible (Medicare and Medicaid) coverage for the over-65 population, we use this to train the **dual-eligible model** to estimate coverage for people in that demographic.
- Second, we re-weight these population estimates by **ambulance risk**, estimated using another model trained on demographic and payer information. The little girl in the first bullet would have a very low risk of needing an ambulance compared with an 85-year old, for example.
- Third, we **match** each WATRS EMS call record with the re-weighted payer mix estimates, based on demographics and geography. This gives us the most probable payer(s) for that specific EMS call.

Summing up these probable payers gives us the "payer mix" for each agency, both by volume and by potential revenue.

Let's talk about each model in more detail.

9.4.1 American Community Survey (ACS) insurance estimates

ACS Public Use Microdata Sample data (PUMS, i.e., data are not aggregated; each line is one person's survey response) are a rich source of information for policy research generally. PUMS at the State level are publicly available,[65] and we've used it frequently to answer numerous health policy questions in the past.

However, information *below* the State level, say, being able to know the County or Census Tract the survey respondent lived in, is highly *restricted*. This means that there are important procedural safeguards to protect the privacy of people who respond to the survey.

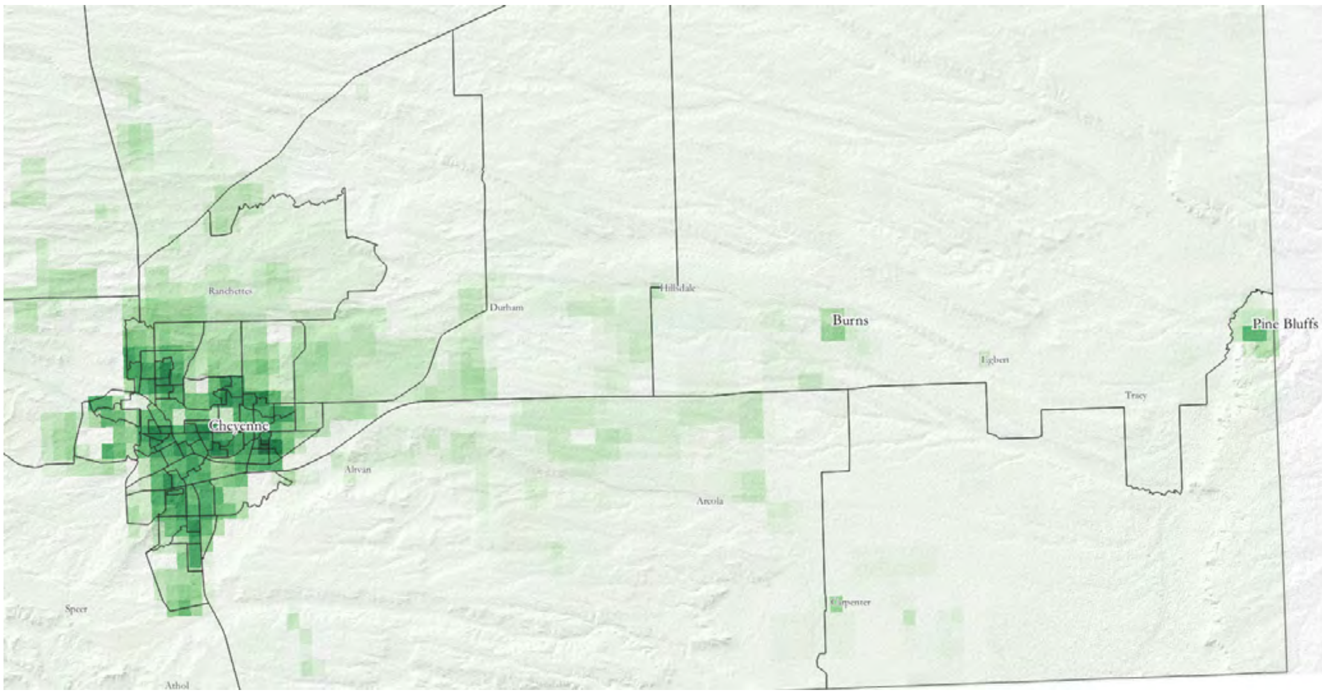
Analyses of restricted data is only possible at secured facilities around the country. Research is done under pre-specified conditions, and any output must clear a Disclosure Review Board before it can be released.

Over the last two years, we were fortunate to be able to collaborate with the U.S. Census Bureau and its Rocky Mountain Federal Statistical Research Data Center (FSRDC) at the University of Colorado[66] in a research project aiming to estimate insurance coverage for Wyoming residents on a very granular level: the 457 Census Block Groups in the State.

[65] https://www.census.gov/programs-surveys/acs/microdata/access.html
[66] https://www.census.gov/about/adrm/fsrdc/locations/rocky-mountain.html

9.4.1.1 What are Census block groups? Census Block Groups are bigger than Census Blocks but smaller than Census Tracts. Figures 18 through 20 show examples of Block Groups around Cheyenne, the Basin, and the Wind River Reservation, respectively. On all figures, we overlay the 2010 Gridded Population estimates to show "where the people are."

Figure 18: Cheyenne area block groups



As you'll note on the figures, using Block Groups as the base level of geography for insurance coverage represents a good balance between granularity and computational complexity. For example, they capture major neighborhoods in bigger cities without needing to model individual blocks. They also capture important features in the rural landscape, like the various components of the Wind River Reservation, or distinguishing between towns like Worland, Powell and Lovell and their surrounding "suburbs."

Figure 19: Basin area block groups

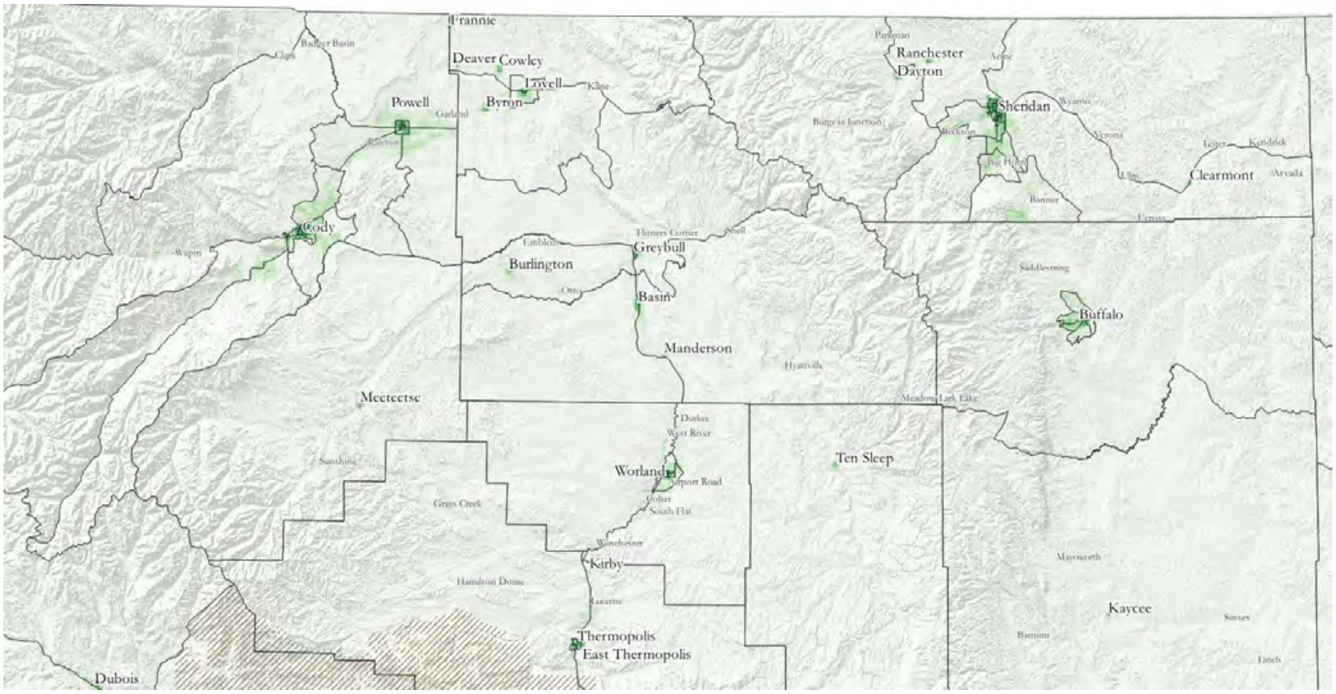
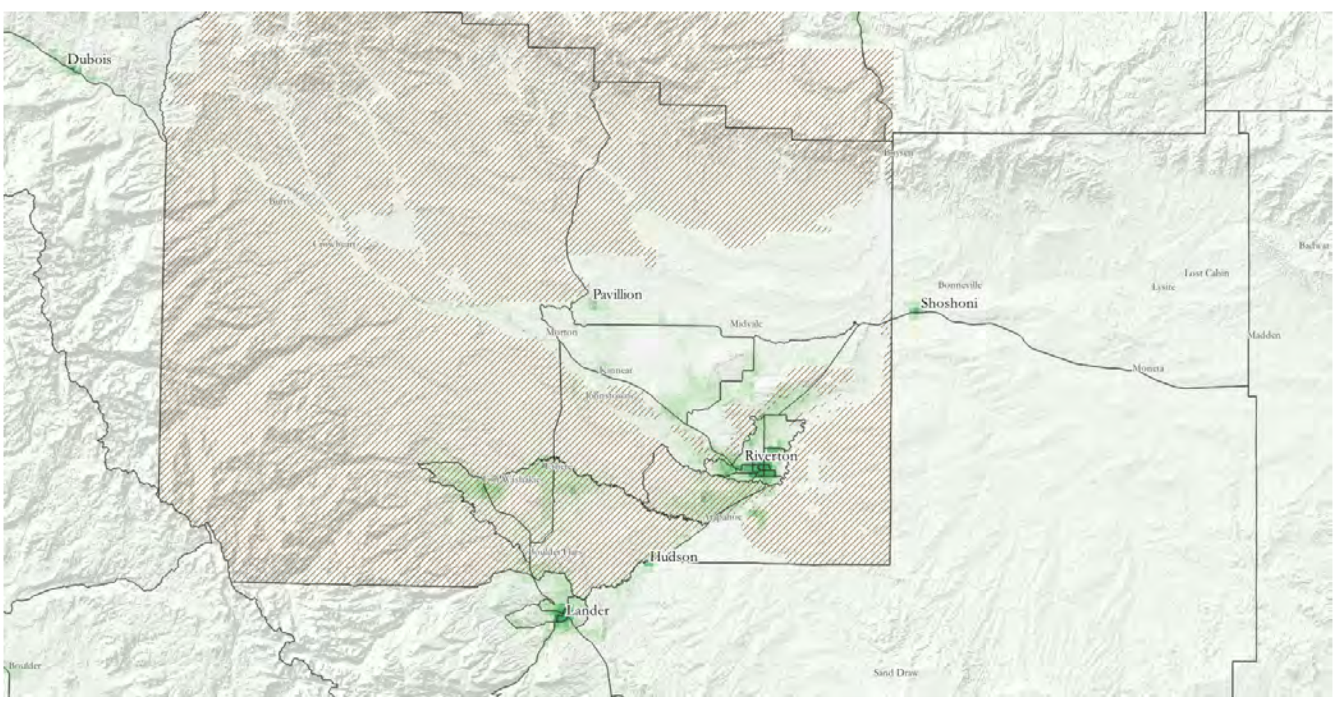


Figure 20: Wind River area block groups



9.4.1.2 Health insurance types

The eight (8) types of insurance coverage estimated include:

- Medicare;
- Medicaid;
- Dual-eligible (i.e., both Medicare and Medicaid);
- Indian Health Service (IHS);
- Veterans' Health Administration or TRICARE;
- Directly-purchased individual insurance ("Obamacare");
- Employer-sponsored health insurance (ESI); and,
- Uninsured / self-pay.

Unfortunately, since people often report multiple forms of coverage in the ACS data, we had to guess what insurance is "primary." To do this, we assumed a hierarchy of payers to recode the insurance variables into these eight groups. Our assumed hierarchy was:

- Medicare ;
- Dual-eligible;
- Medicaid;
- TRICARE/VA;
- ESI;
- Direct;
- IHS;
- Uninsured;

This means, for example, that if someone reported both Medicare and directly-purchased insurance, we would consider their primary to be Medicare, since the directly-purchased insurance would probably be some kind of supplemental Medigap policy. Similarly, if someone reported Medicaid and IHS, we would consider Medicaid to be the primary insurance.

The last category we split up by household income, using 200% FPL as the cutoff and dividing into "Uninsured - lower income" and "Uninsured - middle to upper income" categories, so we end up with 9 total possibilities.

9.4.1.3 Model specification

After pooling multiple years of ACS data, our final model conditioned health insurance coverage type for Wyomingites under 65 based on demographic and geographic factors.

The model specification used a categorical likelihood (e.g., for unordered categories) to predict the specific insurance coverage type $k \in \{\text{Medicaid, Medicare, ...}\}$ for survey respondent i based on a simplex of probabilities $\mathbf{v}_i^k$. This simplex is the result of a softmax transformation, which takes a set of "scores" s_i^k for each insurance type and divides the exponential of that score by the sum of the exponentials of all the scores, like so:

$$\Pr(k|s_i^1, s_i^2, \ldots, s_i^9) = \frac{\exp(s_i^k)}{\sum_{n \in k} \exp(s_i^n)}$$
$$s_i^1 = 0$$

Here, the first score is set to zero to assist with identifiability. The remaining scores are then predicted by a set of geographic and demographic covariates. The specific methodology has yet to go through the Census disclosure process, so we'll stop here.

9.4.1.4 Results What has been disclosed from this modeling effort is a large "look-up table" that estimates the probability of each of the nine insurance types for 71,292 demographic and geographic cells, including:

- 2 sexes;
- 13 5-year age groups from 0 to 65;
- 6 race/ethnicities;
- 457 Census Block Groups;

In addition, the table includes 30 draws from the posterior distribution to illustrate the potential uncertainty, giving 2,138,760 total rows.

The insurance probabilities, per the model, are represented as a simplex (adding up to 100%). For example, 10 of these 30 draws for a 0-5 year old Hispanic male living in a certain Block Group are show in the table below:

Table 192: ACS insurance estimates - example (10 draws, single cell)

Direct	Dual	ESI	IHS	Mcaid	Mcare	TRI/VA	Unins - Low	Unins - Med
10.1%	0.1%	29.3%	0.0%	36.5%	0.2%	9.5%	9.8%	4.5%
27.4%	0.2%	32.4%	0.0%	22.6%	0.1%	5.0%	7.3%	5.1%
17.6%	0.1%	29.1%	0.0%	37.3%	0.0%	1.3%	8.3%	6.3%
15.3%	0.0%	44.0%	0.1%	26.3%	0.3%	6.1%	4.0%	3.8%
16.8%	0.0%	23.1%	0.1%	37.0%	0.1%	7.5%	10.7%	4.7%
18.3%	0.0%	37.8%	0.0%	30.1%	0.1%	3.7%	5.2%	4.5%
26.6%	0.1%	30.3%	0.1%	27.5%	0.0%	3.9%	6.4%	5.1%
19.4%	0.0%	29.8%	0.0%	31.8%	0.1%	7.9%	3.8%	7.2%
20.1%	0.1%	28.3%	0.0%	29.1%	0.0%	9.7%	7.8%	5.0%
12.1%	0.3%	45.3%	0.4%	27.0%	0.1%	7.0%	5.0%	2.8%

9.4.2 Medicare-Medicaid duals

Because the ACS model only looked at Wyomingites under 65, and because Medicaid eligibility data gives us a much more complete and precise look at dual-eligibles, we used a second model to predict these insurance probabilities.

9.4.2.1 Data sources This model is simplified from the ACS model in terms of covariates: we only use 5-year age group, sex, and county. Both race/ethnicity and Block Group data were not available or less reliable in the Medicaid eligibility data.[67]

[67] For example, many Medicaid members report being "Other" as a race, and many use P.O. boxes instead of street addresses.

After summing up the total number of Medicare/Medicaid duals in our eligibility data by these demographic and geographic cells (i.e., "65-69 year old females in Converse County" would be one cell), we merged that "numerator" to the "denominator" of underlying populations for the same cells.[68]

9.4.2.2 Model specification The model then tries to predict the proportion μ_i of dual Medicare/Medicaid members per underlying total population in demographic-geographic cell i using a binomial likelihood. Here, μ_i as a linear function of the individual variables, using a logit link to transform that linear function with domain $(-\infty, \infty)$ into the $[0, 1]$ space of probability:

$$\text{Dual-eligibles}_i \sim \text{Binomial}\left(\mu_i, \text{Population}_i\right)$$
$$\text{logit}(\mu_i) = \alpha + \beta_1 \times \text{Male}_i + \beta_{[\text{Age Group}]} \times \text{Age Group}_i + \beta_{[\text{County}]} \times \text{County}_i$$

9.4.2.3 Results We used the default (flat) priors in the *brms* package, and, after fitting the model using the same MCMC methods described in the Response Time section, we obtain the results below. Coefficients here are not surprising: the "risk" of being a dual eligible increases with age (e.g., needing nursing home care), and is lower in wealthier counties (e.g. Teton, Sublette, Lincoln, Park).

```
 Family: binomial
  Links: mu = logit
Formula: Duals | trials(Count) ~ 1 + Sex + AgeGrp + County
   Data: model_data (Number of observations: 230)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Regression Coefficients:
                 Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept           -2.87      0.07    -3.01    -2.73 1.01      474      678
SexMale             -0.68      0.03    -0.74    -0.62 1.00     2179     1569
AgeGrp70M74         -0.14      0.04    -0.21    -0.07 1.00     1775     1454
AgeGrp75M79         -0.06      0.04    -0.14     0.03 1.00     2179     1740
AgeGrp80M84          0.10      0.05     0.00     0.20 1.00     1739     1516
AgeGrp85P            0.34      0.05     0.25     0.43 1.00     1903     1692
CountyBigHorn        0.53      0.10     0.33     0.73 1.00      630     1134
CountyCampbell       0.10      0.09    -0.07     0.29 1.01      631      933
CountyCarbon        -0.16      0.12    -0.40     0.07 1.01      841     1174
CountyConverse      -0.21      0.13    -0.45     0.03 1.00     1040     1247
CountyCrook         -0.34      0.16    -0.67    -0.04 1.00     1283     1239
CountyFremont        0.70      0.08     0.55     0.86 1.01      520      853
CountyGoshen         0.28      0.11     0.06     0.48 1.01      772     1073
CountyHotSprings     0.69      0.12     0.44     0.92 1.00     1024     1262
CountyJohnson       -0.09      0.13    -0.35     0.16 1.01      946     1281
CountyLaramie        0.22      0.08     0.07     0.37 1.01      481      756
CountyLincoln       -0.31      0.12    -0.54    -0.07 1.00      973     1373
CountyNatrona        0.39      0.08     0.24     0.54 1.01      502      779
CountyNiobrara       0.05      0.21    -0.36     0.44 1.00     1529     1240
CountyPark          -0.11      0.09    -0.30     0.07 1.01      608      839
CountyPlatte         0.10      0.12    -0.13     0.34 1.00      931     1300
CountySheridan       0.11      0.09    -0.06     0.29 1.01      644      936
CountySublette      -1.05      0.20    -1.46    -0.68 1.01     1069     1373
CountySweetwater     0.00      0.09    -0.18     0.19 1.01      681      927
CountyTeton         -1.09      0.15    -1.40    -0.81 1.00     1289     1404
CountyUinta          0.12      0.11    -0.09     0.34 1.01      816     1327
CountyWashakie       0.37      0.12     0.13     0.60 1.00      916      963
CountyWeston         0.18      0.14    -0.10     0.44 1.00      999     1296
```

[68] As maintained by A&I Economic Analysis Division.

```
Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
```

We then use this model to generate a similar lookup table for people over 65.

9.4.3 Post-stratification using 2020 Decennial Census data

At this point, we have a comprehensive look-up table that estimates insurance coverage probabilities for all potential demographic and geographic cells in Wyoming.

The next step is to apply those probabilities to the best possible estimate of *the number of people in each of those cells*. We get that from Wyoming's 2020 Decennial Census, conveniently processed and packaged up by the IPUMS Center for Data Integration at the University of Minnesota.[69]

9.4.4 Ambulance risk

Now we have to re-weight these population estimates by the probability each demographic and payer cell would require an ambulance. As we noted before, kids on private insurance are less likely to need EMS than an 85-year old dual Medicare/Medicaid eligible.

To do this, we need yet another model that estimates the annual count of ambulance trips taken by people based on their age, sex, and insurance coverage.

9.4.4.1 Data processing The interesting problem here is that, while we have excellent data on ground ambulance trips taken by Medicaid and dual-eligible people in Wyoming (because we pay for them), we have to rely on national survey data —specifically the Medical Expenditure Panel Survey (MEPS) —to estimate utilization for other insurance types. MEPS data is not specific to Wyoming, and only includes a limited sample of people, but it's the only data we have for other payers.

- For Medicaid data, we count up the total number of ground EMS trips for all members, including zeros for those that had none. Each row is thus one member, their demographic characteristics, and their annual count of ground ambulance trips.
- For the MEPS data,[70] we combine 2021 and 2022 consolidated data files, keeping ID, sex, race/ethnicity, and insurance coverage type (recoded to primary insurance using the same hierarchy noted in the ACS section). MEPS ambulance trips are recorded in the "other medical expenses" supplementary files, so we merge that in by respondent ID for the same years.

Our final model dataset combines the Medicaid and MEPS data, and includes ID (either de-identified MEPS ID or Medicaid ID), race/ethnicity, sex, age, insurance type, the count of ambulance trips, and then a new variable for the data source (either Medicaid or MEPS).

9.4.4.2 Model specification We ultimately did not include race/ethnicity, due to the problems previously mentioned with Medicaid members self-reporting a lot of the "Other" category.

[69] Steven Manson, Jonathan Schroeder, David Van Riper, Katherine Knowles, Tracy Kugler, Finn Roberts, and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 18.0 [dataset]. Minneapolis, MN: IPUMS. 2023. http://doi.org/10.18128/D050.V18.0

[70] https://meps.ahrq.gov/mepsweb/data_stats/download_data_files.jsp

Additionally, we split the modeling process in half, building one model for people under 65 and one model for over 65.

Both models have the same specification: we estimate the count of ambulance trips reported by (or paid on behalf of) person i, assuming a negative binomial likelihood to account for significant over-dispersion (some people use a lot more ambulance services than others). The negative binomial is parameterized in *brms* using the expected count/mean μ_i and a shape parameter ϕ_i, both of which we condition on the dataset (Medicaid vs. MEPS). The mean is also conditioned on age (modeled as a Gaussian process smooth) and insurance coverage, both as a fixed effect and as a factor-smooth interaction with age.

$$\begin{aligned}
&\text{Ambulance trips}_i \sim \text{Negative binomial}\left(\mu_i, \phi_i\right) \\
&\qquad \log(\mu_i) = \alpha_0 + \beta_1 \times \text{Dataset}_i + \beta_{[\text{Insurance}]} \times \text{Insurance}_i + \text{s}^{gp}(\text{Age}_i, \tau_1) + \text{s}^{fs}(\text{Age}_i, \text{Insurance}_i, \tau_2) \\
&\qquad \log(\phi_i) = \alpha_1 + \beta_2 \times \text{Dataset}_i
\end{aligned}$$

The hope here is to estimate the effects of age and insurance by pooling the two datasets while adjusting for the unique issues resulting from each (e.g., survey vs. claims data), using the overlap in Medicaid and dual-eligibles to pin down the other payers.

The priors we use include:

$$\begin{aligned}
\alpha_0 &\sim \mathcal{N}(0, 3) \\
\alpha_1 &\sim \text{Student}(3, 0, 1) \\
\beta_1, \beta_2 &\sim \text{Student}(3, 0, 1) \\
\beta_{[\text{Insurance}]} &\sim \text{Student}(3, 0, 1) \\
\tau_1, \tau_2 &\sim \text{Student}(3, 0, 1)
\end{aligned}$$

9.4.4.3 Results The results from the under-65 model follow:

```
Family: negbinomial
  Links: mu = log; shape = log
Formula: Ambs ~ 1 + Dataset + INSURANCE + s(AGE, bs = "gp") + s(AGE, INSURANCE, bs = "fs")
         shape ~ 1 + Dataset
   Data: model_under65 (Number of observations: 134744)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smoothing Spline Hyperparameters:
                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(sAGE_1)              1.28      1.45     0.05     5.61 1.00      979      555
sds(sAGEINSURANCE_1)     7.89      1.24     5.86    10.67 1.00      474      850
sds(sAGEINSURANCE_2)     5.94      1.83     3.44    10.47 1.00      754     1053
sds(sAGEINSURANCE_3)     1.74      2.20     0.06     9.17 1.01      441      179

Regression Coefficients:
                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept             -1.89      0.39    -2.72    -1.16 1.02      297      381
shape_Intercept       -2.93      0.03    -2.99    -2.87 1.00     2256     1431
DatasetMEPS           -0.59      0.05    -0.69    -0.48 1.01     2473     1507
INSURANCEMedicaid     -1.26      0.44    -2.03    -0.31 1.02      272      256
INSURANCEMedicare     -0.14      0.65    -1.49     1.10 1.01     1039      943
```

```
INSURANCEPrivate       -2.09      0.47    -2.89    -1.04 1.02      277      150
INSURANCETRICAREVA     -2.15      0.57    -3.29    -1.05 1.02      350      456
INSURANCEUninsured     -2.13      0.54    -3.07    -0.88 1.01      332      199
shape_DatasetMEPS       2.24      0.18     1.93     2.61 1.00     1274     1266
sAGE_1                  0.15      1.39    -2.48     3.23 1.00     2266      882

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
Warning message:
There were 43 divergent transitions after warmup.
Increasing adapt_delta above 0.8 may help.
See http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
```

And for the over 65 model:

```
 Family: negbinomial
  Links: mu = log; shape = log
Formula: Ambs ~ 1 + Dataset + INSURANCE + s(AGE, bs = "gp") + s(AGE, INSURANCE, bs = "fs")
         shape ~ 1 + Dataset
   Data: model_over65 (Number of observations: 19667)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smoothing Spline Hyperparameters:
                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(sAGE_1)              1.65      1.88     0.04     7.17 1.04       96       76
sds(sAGEINSURANCE_1)     0.72      0.56     0.03     2.16 1.00      660      911
sds(sAGEINSURANCE_2)    15.22      6.79     6.77    33.92 1.02      162      112
sds(sAGEINSURANCE_3)     1.09      1.23     0.03     4.06 1.00      879     1027

Regression Coefficients:
                  Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept            -0.82      0.05    -0.92    -0.70 1.01      503      263
shape_Intercept      -2.20      0.04    -2.27    -2.11 1.00     1887     1239
DatasetMEPS          -1.03      0.07    -1.18    -0.89 1.00     1751      984
INSURANCEMedicare    -0.81      0.09    -0.98    -0.63 1.01     1541      989
shape_DatasetMEPS     1.89      0.17     1.58     2.25 1.02      269       76
sAGE_1                0.23      1.82    -2.80     3.62 1.00     1031      596

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).
Warning message:
There were 40 divergent transitions after warmup. Increasing adapt_delta above
0.8 may help.
See http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
```

While there are some divergent transitions in this (and a few previous) models, the posterior predictive check in Figure 21 shows that the model does fit the observed data, and its over-dispersion, well. Note on the figure that we've logged the y-axis, since there were so many folks with 0 to 1 trips, and we really wanted to inspect the tails. Note as well that the Medicaid claims data has a lot more over-dispersion here than the MEPS survey data.

Putting the models together, Figure 22 shows the final results that get moved forward in the analysis — the expected (average) number of trips by age and payer. On the figure, the x-axis shows age, from birth to age 95 and the y-axis shows the average annual count of ambulance trips (note: there is *significan** dispersion around this average; many people have zero, some have over 40). Each line and ribbon shows the average and 90% credible intervals for that specific payer.

A few takeaways from the plot:

Figure 21: Posterior predictive check, under-65 ambulance utilization

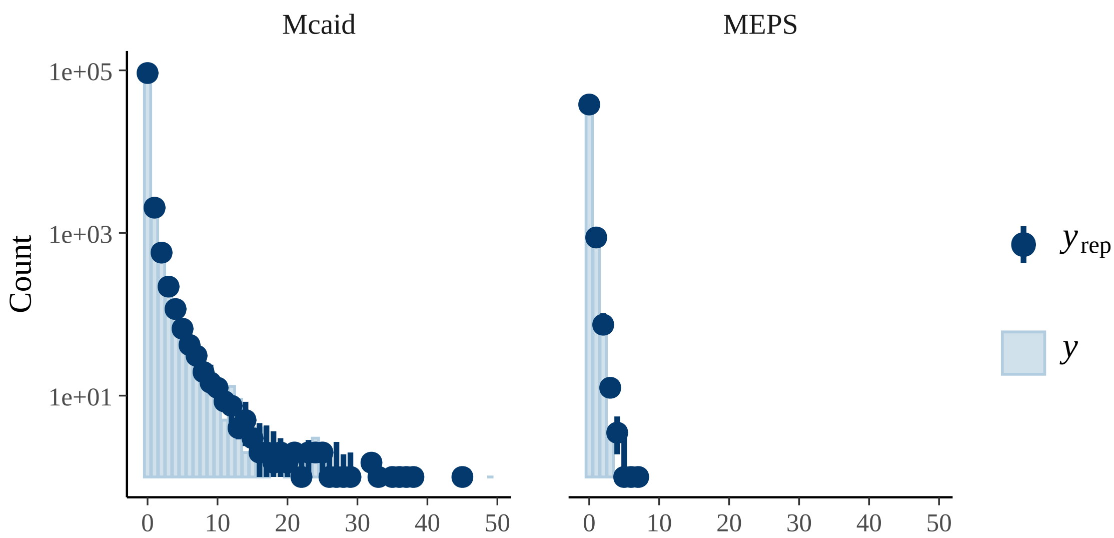
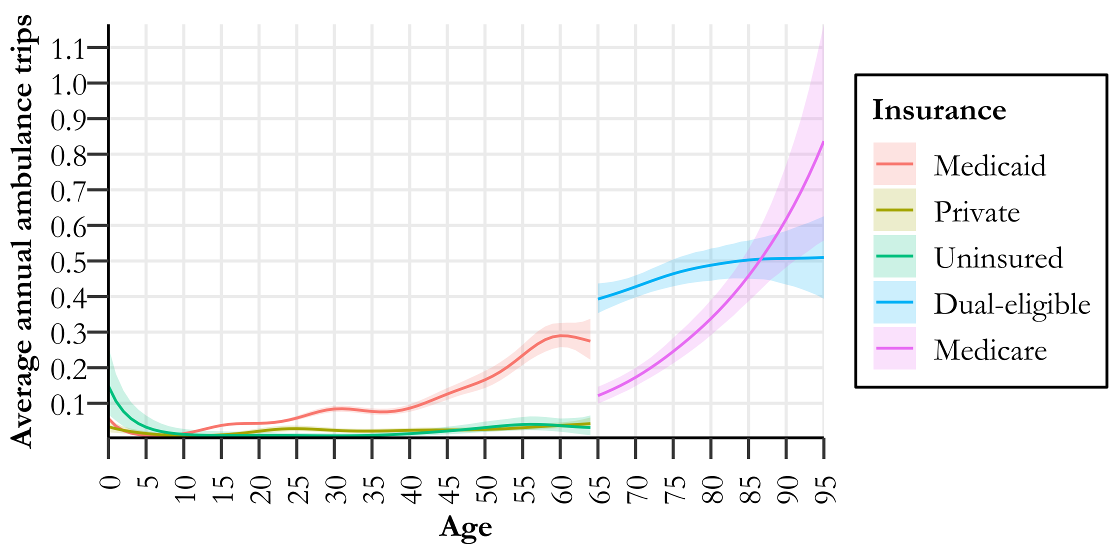


Figure 22: Expected ambulance utilization by age and payer



- As the EMS demographic risk plots show, risk increases with age in a "J-curve."
- Generally speaking, people covered by public payers (e.g. Medicaid, Medicare) have more trips. This is partly because of economics —cost sharing is low to non-existent for Medicaid members, for example —but also because lower-income people tend to be sicker and likely require more ambulance services generally.
- The discontinuity at age 65 resulting from fitting two models with smooths is obvious, but it's not to hard to imagine the Medicaid curve continuing into the dual-eligible one, and the private/uninsured curves going into the Medicare curve —though given the increase in plan generosity when people hit Medicare at 65, some discontinuity might be expected.

9.4.5 Matching with WATRS

Now, we predict the number of ambulance trips each person in the 2020 Decennial Census + payer mix data might have.[71] With the 30 draws from the payer mix model, and additional 10 draws from the ambulance utilization model, we now have a very large list of 300 draws for × 51,000 potential individual ambulance trips, each tagged with demographic, geographic, and payer information.

This is what we use to merge back with the WATRS data, where we know things like age, sex, location, and race/ethnicity, but don't know the payer. To accomplish this, we use a nearest-neighbor matching algorithm from the *MatchIt* package.[72] Specifically, we require exact matches on age group and county, but within those, the algorithm predicts the closest match based on race/ethnicity, Census Block Group, and sex.

At the end, we have a probable payer matched with each known WATRS call. This lets us estimate potential revenue for each service based on the estimated rates.

---

[71] In order to match the ~ 51K annual reimbursed transports in WATRS, we adjust the predicted ambulance rate upwards by a factor of 1.18.

[72] Ho D, Imai K, King G, Stuart E (2011). "MatchIt: Nonparametric Preprocessing for Parametric Causal Inference." Journal of Statistical Software, 42(8), 1–28. doi:10.18637/jss.v042.i08.

9.5 Highway crash volume

9.5.1 Data processing

First, we imported and cleaned data provided by the Wyoming Department of Transportation (WYDOT) cataloging all vehicle accidents between 2014 and 2024. Important variables for analysis included:

- The date/time of the crash;
- The location in terms of latitude/longitude;
- The crash severity; and,
- Timestamps on when EMS was notified and when the service arrived.

Using the open-source Geographic Information System (GIS) software QGIS,[73] we pruned a WYDOT road shapefile[74] to just include major state highways, and then created a 10-meter buffer around each highway segment. A geographic merge between this file and the accident data gave us the standard WYDOT highway names (e.g. "ML80" for I-80) for each accident report.

We then merged WYDOT Annual Average Daily Traffic (AADT) estimates with ELRS Milepost shapefiles to estimate annual traffic passing through each milepost in the highway system. In some cases, we had to use the Excel Vehicle Miles book to fill in some gaps in the AADT shapefile.

For accident volume, we merged the accident data to the milepost data (e.g., based on standard ELRS identifier and milemarker), filled in any missing values with zeros (assuming all accidents were reported), and then aggregated accidents for the 10-year period between 2014 and 2024. Importantly, we only used 2023 AADT information, so this makes the simplifying and potentially strong assumption that traffic has been at 2023 levels over that entire time period.

9.5.2 Model specification

The crash volume and risk estimates came from a single model, which attempts to smooth the average annual count of accidents by milemarker for the major highways in the State. As the charts for selected highways indicate, we are finding a wiggly line along each route that best fits the observed data.

Specifically, we model the 10-year average annual number of accidents occurring at milemarker i on route j using a Poisson distribution. The rate parameter λ_{ij} for that particular place is estimated using a route-specific varying intercept α_j that is shrunk towards the overall highway system mean $\bar{\alpha}$ in cases where accident data is more sparse. That sets the overall average number of accidents for each route. Within routes, we estimate the difference across milemarkers using a Gaussian process smooth (wiggly line), assuming a Matern covariance kernel and a range parameter ρ of 5 miles. Finally, we include an offset (parameter constrained to 1) for average annual vehicle traffic passing through that particular area to be able to estimate the risk.

[73] QGIS.org, 3.34. QGIS Geographic Information System. QGIS Association. http://www.qgis.org
[74] https://gis.wyoroad.info/

$$
\begin{aligned}
\text{Avg. accidents}_{ij} &\sim \text{Poisson}\left(\lambda_{ij}\right) \\
\log(\lambda_{ij}) &= \alpha_j + \text{s}^{gp}_{\rho=5}(\text{Milepost}_i, \text{by Route}_j, \tau_j) + \text{offset}(\log(\text{AADT}_{ij})) \\
\alpha_j &\sim \mathcal{N}(\bar{\alpha}, \sigma) \\
\bar{\alpha} &\sim \text{Student}(3, 0, 0.5) \\
\sigma &\sim \text{Student}(3, 0, 0.25) \\
\tau_j &\sim \text{Student}(3, 0, 0.5)
\end{aligned}
$$

9.5.3 Results

When fitted on the WYDOT data using the same MCMC techniques described previously, the model results are as follows. We recognize this massive list of parameter estimates is not particularly helpful; instead, we'd recommend inspecting how well the trends in Figure 7 fit the observed data (hollow dots).

```
 Family: poisson
  Links: mu = log
Formula: Accidents ~ 1 + (1 | ROUTE) + s(MILEPOST, bs = "gp", k = 50, m = c(3, 5), by = ROUTE) +
                     offset(log(AADT))
   Data: accid_all_yrs (Number of observations: 5683)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smoothing Spline Hyperparameters:
                            Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(sMILEPOSTROUTEML10_1)     103.45     24.95    64.26   162.91 1.01      796      958
sds(sMILEPOSTROUTEML1002_1)     0.56      0.61     0.02     2.18 1.00     2356      888
sds(sMILEPOSTROUTEML1006_1)     0.55      0.58     0.01     2.07 1.00     2640      966
sds(sMILEPOSTROUTEML103_1)      0.56      0.64     0.02     2.12 1.00     2888     1042
sds(sMILEPOSTROUTEML107_1)      0.56      0.68     0.02     2.24 1.00     2010      818
sds(sMILEPOSTROUTEML109_1)      0.54      0.60     0.02     1.93 1.00     2359     1172
sds(sMILEPOSTROUTEML11_1)       0.71      2.59     0.02     2.07 1.01     1616     1007
sds(sMILEPOSTROUTEML1118_1)     0.55      0.60     0.02     2.09 1.00     2418      943
sds(sMILEPOSTROUTEML12_1)       0.55      0.64     0.01     2.10 1.00     2681      975
sds(sMILEPOSTROUTEML1202_1)     0.55      0.56     0.02     1.91 1.00     2426      879
sds(sMILEPOSTROUTEML13_1)      43.43     15.31     0.49    73.73 1.06       70       25
sds(sMILEPOSTROUTEML1310_1)     0.54      0.58     0.01     2.01 1.00     2336      620
sds(sMILEPOSTROUTEML14_1)       0.53      0.66     0.02     1.98 1.00     2555     1063
sds(sMILEPOSTROUTEML1400_1)     0.54      0.65     0.02     2.13 1.00     2459      984
sds(sMILEPOSTROUTEML1401_1)     0.56      0.68     0.02     2.10 1.00     1954      927
sds(sMILEPOSTROUTEML15_1)       0.54      0.58     0.02     2.06 1.00     2855     1188
sds(sMILEPOSTROUTEML1502_1)     0.57      0.65     0.02     2.23 1.00     2496      767
sds(sMILEPOSTROUTEML1507_1)     0.57      0.86     0.02     2.23 1.01     1572      569
sds(sMILEPOSTROUTEML16_1)       0.58      1.14     0.02     1.99 1.00     1826      836
sds(sMILEPOSTROUTEML1602_1)     0.55      0.57     0.02     2.13 1.00     2066     1294
sds(sMILEPOSTROUTEML17_1)       0.54      0.54     0.02     1.94 1.00     2873     1083
sds(sMILEPOSTROUTEML18_1)       0.56      0.62     0.01     2.22 1.00     2452     1004
sds(sMILEPOSTROUTEML1801_1)     0.57      0.70     0.02     2.09 1.00     2156      702
sds(sMILEPOSTROUTEML1900_1)     0.54      0.57     0.02     2.00 1.00     2232      863
sds(sMILEPOSTROUTEML1903_1)     0.54      0.54     0.02     2.00 1.01     3149      983
sds(sMILEPOSTROUTEML1906_1)     0.54      0.64     0.02     1.88 1.00     2160      862
sds(sMILEPOSTROUTEML1912_1)     0.55      0.74     0.02     2.06 1.00     1775      709
sds(sMILEPOSTROUTEML1915_1)     0.57      0.68     0.02     2.07 1.01     2989      774
sds(sMILEPOSTROUTEML20_1)      25.49     11.27     0.29    49.20 1.05      109       23
sds(sMILEPOSTROUTEML200_1)      0.57      0.78     0.02     2.08 1.00     2292     1083
sds(sMILEPOSTROUTEML201_1)      0.54      0.55     0.02     2.00 1.00     2086     1024
sds(sMILEPOSTROUTEML202_1)      0.55      0.59     0.02     2.14 1.00     2203     1049
sds(sMILEPOSTROUTEML21_1)       4.46     14.08     0.02    54.41 1.02      213       80
sds(sMILEPOSTROUTEML2100_1)     0.55      0.64     0.02     2.12 1.00     1821      910
sds(sMILEPOSTROUTEML2103_1)     0.53      0.56     0.02     1.87 1.00     2148      887
```

```
sds(sMILEPOSTROUTEML211_1)       0.54      0.63     0.02     2.00 1.01     2178      874
sds(sMILEPOSTROUTEML22_1)        0.54      0.62     0.02     2.12 1.00     2531     1117
sds(sMILEPOSTROUTEML2200_1)      0.54      0.57     0.02     1.93 1.00     1928      733
sds(sMILEPOSTROUTEML2203_1)      0.55      0.60     0.02     2.03 1.00     3163     1139
sds(sMILEPOSTROUTEML23_1)       75.94     27.30    36.45   143.22 1.00      552     1037
sds(sMILEPOSTROUTEML2300_1)      0.55      0.65     0.01     2.13 1.00     2004      898
sds(sMILEPOSTROUTEML2302_1)      0.53      0.71     0.02     1.71 1.00     2498     1009
sds(sMILEPOSTROUTEML2303_1)      0.52      0.54     0.02     1.91 1.00     2371      975
sds(sMILEPOSTROUTEML24_1)        0.56      0.62     0.02     2.11 1.00     2539      937
sds(sMILEPOSTROUTEML25_1)       27.70      5.34    18.55    39.45 1.01      616     1096
sds(sMILEPOSTROUTEML26_1)        3.20     13.09     0.01    46.85 1.03      354       95
sds(sMILEPOSTROUTEML27_1)        0.55      0.65     0.02     2.08 1.00     2151      824
sds(sMILEPOSTROUTEML29_1)       58.05     29.05     0.61   133.12 1.05       67       17
sds(sMILEPOSTROUTEML30_1)        0.56      0.63     0.02     2.33 1.00     2568      758
sds(sMILEPOSTROUTEML300_1)       0.62      1.09     0.02     2.30 1.00     2427      813
sds(sMILEPOSTROUTEML302_1)       0.57      1.05     0.02     2.00 1.00     2396     1087
sds(sMILEPOSTROUTEML303_1)       0.54      0.62     0.02     2.11 1.00     1988      850
sds(sMILEPOSTROUTEML31_1)        3.61     14.22     0.02    57.51 1.04      276       36
sds(sMILEPOSTROUTEML33_1)        0.53      0.56     0.02     1.91 1.00     2185     1019
sds(sMILEPOSTROUTEML34_1)        8.62     10.55     0.04    30.80 1.08       51      409
sds(sMILEPOSTROUTEML35_1)        0.56      0.60     0.02     2.21 1.00     3179     1076
sds(sMILEPOSTROUTEML352_1)       0.57      0.75     0.02     2.17 1.00     3162     1179
sds(sMILEPOSTROUTEML36_1)       58.91     15.74    34.37    96.36 1.00      827     1111
sds(sMILEPOSTROUTEML37_1)        6.85     16.80     0.02    59.59 1.15       19       24
sds(sMILEPOSTROUTEML374_1)       0.54      0.54     0.02     1.97 1.00     2505     1045
sds(sMILEPOSTROUTEML38_1)        0.56      0.63     0.02     2.20 1.00     3099     1062
sds(sMILEPOSTROUTEML39_1)        0.54      0.61     0.02     2.22 1.00     1868     1062
sds(sMILEPOSTROUTEML40_1)        0.55      0.61     0.02     2.04 1.00     2392      861
sds(sMILEPOSTROUTEML401_1)       0.55      0.62     0.01     2.06 1.00     2002      710
sds(sMILEPOSTROUTEML42_1)        0.55      0.61     0.02     2.16 1.00     2251      842
sds(sMILEPOSTROUTEML43_1)       22.99      7.06    12.06    39.83 1.00     1175     1365
sds(sMILEPOSTROUTEML44_1)        1.14      7.89     0.01     2.33 1.00     1173      486
sds(sMILEPOSTROUTEML46_1)        0.59      1.38     0.02     1.93 1.00     2070     1029
sds(sMILEPOSTROUTEML48_1)        0.54      0.57     0.02     1.99 1.00     1465      769
sds(sMILEPOSTROUTEML502_1)       0.55      0.60     0.02     2.05 1.00     2415      938
sds(sMILEPOSTROUTEML60_1)        0.60      0.72     0.02     2.39 1.00     2158     1070
sds(sMILEPOSTROUTEML600_1)       0.57      1.21     0.02     1.98 1.00     1964      988
sds(sMILEPOSTROUTEML601_1)       0.55      0.59     0.02     2.04 1.00     2609      912
sds(sMILEPOSTROUTEML604_1)       0.55      0.69     0.01     2.10 1.00     1899      853
sds(sMILEPOSTROUTEML607_1)       0.81      3.01     0.01     2.63 1.00     1678      717
sds(sMILEPOSTROUTEML6792_1)      0.54      0.58     0.03     2.00 1.00     1822     1093
sds(sMILEPOSTROUTEML707_1)       0.55      0.60     0.02     2.13 1.00     2111     1121
sds(sMILEPOSTROUTEML708_1)       0.54      0.58     0.02     2.04 1.00     1879      796
sds(sMILEPOSTROUTEML710_1)       0.54      0.55     0.02     1.98 1.00     2180     1062
sds(sMILEPOSTROUTEML77_1)        0.56      0.64     0.02     2.17 1.00     2514      817
sds(sMILEPOSTROUTEML80_1)       23.94      3.44    17.72    31.30 1.00      658     1186
sds(sMILEPOSTROUTEML803_1)       0.54      0.58     0.02     1.91 1.00     2345     1098
sds(sMILEPOSTROUTEML85_1)        0.74      1.67     0.01     3.41 1.00     1393      608
sds(sMILEPOSTROUTEML90_1)       22.12      5.63    12.55    34.79 1.00     1015     1413
sds(sMILEPOSTROUTEML91_1)        0.55      0.66     0.02     1.85 1.00     2183      909

Multilevel Hyperparameters:
~ROUTE (Number of levels: 85)
              Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sd(Intercept)     0.37      0.04     0.30     0.46 1.01      353      857

Regression Coefficients:
                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
Intercept                 -7.55      0.05    -7.65    -7.46 1.00      421      692
sMILEPOST:ROUTEML10_1     -0.02      0.68    -1.39     1.36 1.01     3116     1144
sMILEPOST:ROUTEML1002_1    0.02      0.73    -1.50     1.55 1.01     1756      925
sMILEPOST:ROUTEML1006_1   -0.02      0.76    -1.70     1.55 1.00     1814      770
sMILEPOST:ROUTEML103_1    -0.01      0.71    -1.56     1.44 1.00     2921     1323
sMILEPOST:ROUTEML107_1     0.00      0.74    -1.33     1.41 1.00     2153      852
sMILEPOST:ROUTEML109_1    -0.03      0.82    -1.59     1.45 1.00     1796      626
sMILEPOST:ROUTEML11_1     -0.04      0.80    -1.82     1.38 1.01     1280      387
sMILEPOST:ROUTEML1118_1   -0.02      0.78    -1.54     1.38 1.01     3450     1051
sMILEPOST:ROUTEML12_1     -0.27      1.86    -6.97     1.78 1.05      240       52
```

sMILEPOST:ROUTEML1202_1	0.04	0.84	-1.43	1.70	1.00	1626	652
sMILEPOST:ROUTEML13_1	-0.00	0.81	-1.62	1.67	1.01	1488	734
sMILEPOST:ROUTEML1310_1	-0.03	0.74	-1.58	1.41	1.00	2767	890
sMILEPOST:ROUTEML14_1	-0.00	0.70	-1.39	1.41	1.00	2164	1038
sMILEPOST:ROUTEML1400_1	0.02	0.76	-1.59	1.72	1.01	3058	1008
sMILEPOST:ROUTEML1401_1	0.06	0.91	-1.49	1.90	1.01	1459	330
sMILEPOST:ROUTEML15_1	0.06	0.99	-1.54	1.86	1.01	1147	375
sMILEPOST:ROUTEML1502_1	0.02	0.99	-1.78	1.85	1.00	1073	496
sMILEPOST:ROUTEML1507_1	0.01	0.84	-1.48	1.66	1.01	3025	815
sMILEPOST:ROUTEML16_1	0.01	0.79	-1.55	1.76	1.01	2124	753
sMILEPOST:ROUTEML1602_1	0.02	0.72	-1.35	1.40	1.00	1814	882
sMILEPOST:ROUTEML17_1	-0.03	0.74	-1.49	1.36	1.01	2047	987
sMILEPOST:ROUTEML18_1	0.00	0.84	-1.73	1.83	1.00	942	681
sMILEPOST:ROUTEML1801_1	-0.04	0.78	-1.77	1.32	1.01	2556	834
sMILEPOST:ROUTEML1900_1	-0.02	0.87	-1.47	1.43	1.00	1292	571
sMILEPOST:ROUTEML1903_1	-0.01	0.76	-1.55	1.54	1.00	1873	857
sMILEPOST:ROUTEML1906_1	-0.00	0.77	-1.59	1.60	1.01	2624	792
sMILEPOST:ROUTEML1912_1	0.04	0.70	-1.36	1.53	1.00	3221	1088
sMILEPOST:ROUTEML1915_1	-0.06	0.84	-1.70	1.37	1.01	1810	585
sMILEPOST:ROUTEML20_1	0.00	0.73	-1.52	1.45	1.00	2186	806
sMILEPOST:ROUTEML200_1	0.03	0.89	-1.76	1.81	1.01	1782	467
sMILEPOST:ROUTEML201_1	0.01	0.71	-1.47	1.63	1.00	2149	843
sMILEPOST:ROUTEML202_1	0.03	0.94	-1.64	1.91	1.01	1965	715
sMILEPOST:ROUTEML21_1	-0.04	0.88	-1.60	1.50	1.01	929	376
sMILEPOST:ROUTEML2100_1	0.08	1.00	-1.62	2.13	1.01	925	289
sMILEPOST:ROUTEML2103_1	-0.02	0.88	-1.71	1.53	1.02	1320	415
sMILEPOST:ROUTEML211_1	-0.02	0.77	-1.54	1.58	1.01	2957	1074
sMILEPOST:ROUTEML22_1	-0.02	0.84	-1.54	1.42	1.00	1658	844
sMILEPOST:ROUTEML2200_1	0.01	0.75	-1.53	1.64	1.01	1901	813
sMILEPOST:ROUTEML2203_1	0.02	0.78	-1.47	1.68	1.01	2064	605
sMILEPOST:ROUTEML23_1	-0.01	0.87	-1.55	1.71	1.02	1666	654
sMILEPOST:ROUTEML2300_1	0.03	0.73	-1.28	1.46	1.00	1798	922
sMILEPOST:ROUTEML2302_1	-0.04	0.78	-1.66	1.47	1.00	1957	752
sMILEPOST:ROUTEML2303_1	-0.15	1.56	-2.76	1.84	1.02	345	91
sMILEPOST:ROUTEML24_1	-0.01	0.77	-1.57	1.51	1.01	1368	484
sMILEPOST:ROUTEML25_1	-0.02	0.75	-1.49	1.50	1.00	1264	665
sMILEPOST:ROUTEML26_1	-0.01	0.88	-1.49	1.50	1.01	2200	814
sMILEPOST:ROUTEML27_1	-0.03	0.83	-1.78	1.53	1.00	1784	794
sMILEPOST:ROUTEML29_1	0.02	0.79	-1.45	1.62	1.01	1768	809
sMILEPOST:ROUTEML30_1	-0.02	0.77	-1.55	1.48	1.00	1890	717
sMILEPOST:ROUTEML300_1	0.01	0.80	-1.54	1.63	1.00	1398	594
sMILEPOST:ROUTEML302_1	-0.00	0.74	-1.62	1.47	1.00	1741	814
sMILEPOST:ROUTEML303_1	0.04	0.98	-1.56	1.63	1.01	1038	451
sMILEPOST:ROUTEML31_1	-0.01	0.77	-1.57	1.39	1.01	2197	699
sMILEPOST:ROUTEML33_1	0.01	0.86	-1.67	1.83	1.00	1475	609
sMILEPOST:ROUTEML34_1	0.03	0.88	-1.76	1.89	1.00	2022	737
sMILEPOST:ROUTEML35_1	0.01	0.74	-1.51	1.61	1.01	2830	1179
sMILEPOST:ROUTEML352_1	-0.03	0.79	-1.83	1.42	1.00	2675	712
sMILEPOST:ROUTEML36_1	0.02	0.76	-1.56	1.68	1.00	2308	825
sMILEPOST:ROUTEML37_1	-0.03	0.77	-1.62	1.33	1.01	1476	642
sMILEPOST:ROUTEML374_1	0.06	0.86	-1.44	1.98	1.00	1061	404
sMILEPOST:ROUTEML38_1	0.00	0.76	-1.50	1.52	1.00	2042	792
sMILEPOST:ROUTEML39_1	0.06	0.91	-1.59	2.12	1.01	1390	481
sMILEPOST:ROUTEML40_1	-0.04	0.85	-1.77	1.56	1.01	1914	749
sMILEPOST:ROUTEML401_1	0.01	0.70	-1.39	1.39	1.00	3014	1093
sMILEPOST:ROUTEML42_1	-0.05	0.79	-1.73	1.34	1.00	1446	665
sMILEPOST:ROUTEML43_1	0.12	1.84	-1.94	2.09	1.03	589	199
sMILEPOST:ROUTEML44_1	-0.06	0.97	-1.78	1.52	1.01	1319	654
sMILEPOST:ROUTEML46_1	0.03	0.73	-1.41	1.67	1.00	1812	699
sMILEPOST:ROUTEML48_1	-0.04	0.81	-1.96	1.58	1.02	1467	529
sMILEPOST:ROUTEML502_1	-0.03	0.72	-1.60	1.38	1.00	1749	861
sMILEPOST:ROUTEML60_1	-0.03	0.75	-1.62	1.42	1.01	1862	652
sMILEPOST:ROUTEML600_1	-0.00	0.84	-1.70	1.66	1.00	1642	904
sMILEPOST:ROUTEML601_1	-0.04	0.83	-1.82	1.63	1.01	1650	623
sMILEPOST:ROUTEML604_1	0.01	0.72	-1.49	1.52	1.00	2083	942
sMILEPOST:ROUTEML607_1	-0.00	0.74	-1.58	1.43	1.00	2208	863
sMILEPOST:ROUTEML6792_1	0.01	0.97	-1.63	1.79	1.00	1304	603
sMILEPOST:ROUTEML707_1	-0.02	1.21	-1.79	1.97	1.00	986	364

```
sMILEPOST:ROUTEML708_1      0.00       0.83    -1.54      1.59 1.00      2020       745
sMILEPOST:ROUTEML710_1      0.01       0.93    -1.64      1.79 1.01      1409       420
sMILEPOST:ROUTEML77_1      -0.00       0.76    -1.52      1.46 1.01      1087       477
sMILEPOST:ROUTEML80_1       0.06       0.75    -1.38      1.60 1.00      2005       952
sMILEPOST:ROUTEML803_1      0.00       0.69    -1.49      1.41 1.00      2781      1009
sMILEPOST:ROUTEML85_1       0.03       0.80    -1.56      1.69 1.00      1596       655
sMILEPOST:ROUTEML90_1       0.07       0.85    -1.43      1.97 1.02      1344       607
sMILEPOST:ROUTEML91_1       0.23       2.00    -1.50      3.51 1.02       284        89

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).

Warning message:
Parts of the model have not converged (some Rhats are > 1.05).
Be careful when analysing the results!
We recommend running more iterations and/or setting stronger priors.
```

9.6 Highway EMS response time

This model was more challenging to fit, and required significantly more structure than the volume/risk model. The primary reason is that EMS response times can't be estimated in a vacuum (i.e., using the highway data alone), particularly for routes where accidents are rare and data is sparse. If there was only one accident on a small route, for example, and it happened to occur very early in the morning or when an EMS service was busy, the response time estimated for that route might be wildly high.

We therefore add in a known factor to stabilize our estimates: the "Google maps" drive time from that particular milemarker to the nearest ground ambulance location.

9.6.1 Data processing

This is fairly minimal. Instead of looking at counts of accidents, we start with the raw WYDOT data, which show one crash per row.

After tagging each route with the WYDOT ELRS identifier using the GIS techniques mentioned in the previous section, we then add the calculated "Google maps"[75] drive time from the incident to the closest potential ambulance location.

9.6.2 Model specification

To model EMS response times, we use an exponentially-modified Gaussian, which is a skewed distribution commonly used in modeling reaction times.[76] We assume the average response time to call i in the WYDOT data is the sum of two separate, but unobserved components:

- The *chute time*, which is the time it takes to dispatch the ambulance; and,
- The *drive time* to the call itself.

We model these separately, because they are likely influenced by different factors.

[75] We use this term a lot to give you a sense of what this is, but the drive times are actually calculated using Open Street Map data, as previously noted.

[76] There is no other theoretical reason here; it just fits the data well. See https://lindeloev.github.io/shiny-rt/ for an interactive explanation of various reaction time models.

$$
\begin{aligned}
\text{EMS response time}_i &\sim \text{Exponentially-modified Gaussian}(\mu_i, \sigma, \beta) \\
\mu_i &= \text{Chute time}_i + \delta_i \times \text{Drive time to closest ambulance from milemarker}_i \\
\text{Chute time}_i &= \alpha_0 + \text{s}^{cc}(\text{Hour of the day}_i, \tau_1) \\
\delta_i &= \alpha_1 + \text{s}^{cc}(\text{Month of year}_i, \tau_2) + s^{gp}_{\rho=5}(\text{Milepost}_i, \text{by Route}, \tau_3)
\end{aligned}
$$

Here, the average chute time is a function of an overall intercept (α_0) plus variation based on the hour of the day when call i occurred —which we model as a cyclic smooth ("cc") so that 23:59 and 00:00 refer to similar times of the day.

The second component, the average drive time to call i, is the result of a factor δ_i multiplied to the calculated "Google maps" drive time from the milemarker where call i occurred and the closest ambulance location. In other words, that calculated estimate should be close to the actual drive time, but might vary up or down based on things like:

- The month of the year (another cyclic smooth so months 1 and 12 'line up'), which attempts to adjust for seasonal conditions; and,
- And any route-specific deviations from the calculated time, modeled as a Gaussian process smooth for each route using the same range parameter ($\rho = 5$ miles) as the previous highway model.

As with most of the models in this report, we use regularizing priors like the Student$(3, 0, 1)$. We have also used a few informative priors, like the average chute time α_0 being around 5 minutes, but ranging from 0 to 10 minutes):

$$
\begin{aligned}
\alpha_0 &\sim \mathcal{N}(5, 2) \\
\alpha_1 &\sim \mathcal{N}(1, 1) \\
\tau_1 \dots \tau_3 &\sim \text{Student}(3, 0, 1) \\
\beta &\sim \text{Gamma}(1, 0.1) \\
\sigma &\sim \text{Student}(3, 0, 10.4)
\end{aligned}
$$

9.6.3 Results

We append the model output below, recognizing it is less than helpful. Figure 5 shows the final product, and the results are intuitive.

```
Family: exgaussian
  Links: mu = identity; sigma = identity; beta = identity
Formula: Time ~ chute + drive * Duration
         chute ~ 1 + s(HoD, bs = "cc", k = 5)
         drive ~ 1 + s(MoY, bs = "cc", k = 5) + s(MILEPOST, bs = "gp", m = c(-3, 5), by = ROUTE)
   Data: resp_dist (Number of observations: 8250)
  Draws: 4 chains, each with iter = 1000; warmup = 500; thin = 1;
         total post-warmup draws = 2000

Smoothing Spline Hyperparameters:
                                   Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sds(chute_sHoD_1)                      0.66      0.35     0.26     1.60 1.01      895     1312
```

sds(drive_sMoY_1)	0.05	0.05	0.02	0.20	1.01	647	943
sds(drive_sMILEPOSTROUTEML10_1)	0.89	0.39	0.37	1.86	1.01	670	1233
sds(drive_sMILEPOSTROUTEML1002_1)	0.72	0.74	0.02	2.28	1.01	1519	758
sds(drive_sMILEPOSTROUTEML1006_1)	0.59	0.55	0.02	1.97	1.00	1103	869
sds(drive_sMILEPOSTROUTEML103_1)	0.95	0.50	0.37	2.25	1.00	1654	1512
sds(drive_sMILEPOSTROUTEML107_1)	1.23	0.67	0.30	2.91	1.00	972	823
sds(drive_sMILEPOSTROUTEML109_1)	0.33	0.31	0.01	1.17	1.00	1021	991
sds(drive_sMILEPOSTROUTEML11_1)	0.79	0.50	0.06	1.99	1.01	532	520
sds(drive_sMILEPOSTROUTEML1118_1)	0.88	0.64	0.07	2.54	1.00	1152	994
sds(drive_sMILEPOSTROUTEML12_1)	1.20	0.57	0.35	2.57	1.01	603	663
sds(drive_sMILEPOSTROUTEML1202_1)	0.80	0.82	0.03	2.80	1.00	1773	1022
sds(drive_sMILEPOSTROUTEML13_1)	1.61	0.66	0.82	3.38	1.00	948	1260
sds(drive_sMILEPOSTROUTEML14_1)	0.67	0.37	0.23	1.59	1.01	803	294
sds(drive_sMILEPOSTROUTEML1400_1)	0.68	0.69	0.02	2.55	1.00	998	259
sds(drive_sMILEPOSTROUTEML1401_1)	0.72	0.75	0.03	2.71	1.00	860	269
sds(drive_sMILEPOSTROUTEML15_1)	1.27	0.86	0.10	3.22	1.01	629	889
sds(drive_sMILEPOSTROUTEML1502_1)	0.31	0.35	0.01	1.28	1.00	898	955
sds(drive_sMILEPOSTROUTEML1507_1)	0.73	0.57	0.12	2.27	1.00	981	736
sds(drive_sMILEPOSTROUTEML16_1)	1.22	0.63	0.49	2.66	1.00	1195	1065
sds(drive_sMILEPOSTROUTEML1602_1)	1.58	1.30	0.06	4.40	1.00	651	639
sds(drive_sMILEPOSTROUTEML17_1)	0.56	0.59	0.02	2.00	1.01	1208	1054
sds(drive_sMILEPOSTROUTEML18_1)	0.97	1.02	0.08	3.36	1.00	724	691
sds(drive_sMILEPOSTROUTEML1801_1)	0.70	0.63	0.02	2.34	1.00	971	946
sds(drive_sMILEPOSTROUTEML1900_1)	0.83	0.55	0.17	2.25	1.01	776	452
sds(drive_sMILEPOSTROUTEML1903_1)	6.81	2.61	3.27	13.42	1.01	799	1257
sds(drive_sMILEPOSTROUTEML1906_1)	0.45	0.41	0.02	1.49	1.00	861	822
sds(drive_sMILEPOSTROUTEML1912_1)	0.75	0.60	0.05	2.30	1.00	1021	999
sds(drive_sMILEPOSTROUTEML1915_1)	0.67	0.64	0.02	2.32	1.00	1177	970
sds(drive_sMILEPOSTROUTEML20_1)	0.32	0.21	0.06	0.84	1.00	488	589
sds(drive_sMILEPOSTROUTEML200_1)	0.67	0.60	0.03	2.20	1.00	1134	822
sds(drive_sMILEPOSTROUTEML201_1)	0.55	0.59	0.01	2.11	1.00	881	825
sds(drive_sMILEPOSTROUTEML202_1)	0.86	0.62	0.04	2.46	1.01	716	444
sds(drive_sMILEPOSTROUTEML21_1)	0.93	0.55	0.18	2.36	1.01	397	380
sds(drive_sMILEPOSTROUTEML2100_1)	1.50	1.22	0.06	4.40	1.00	906	789
sds(drive_sMILEPOSTROUTEML2103_1)	1.02	1.07	0.03	3.52	1.01	2441	1091
sds(drive_sMILEPOSTROUTEML211_1)	0.88	0.62	0.10	2.41	1.00	895	615
sds(drive_sMILEPOSTROUTEML22_1)	1.18	0.70	0.10	2.82	1.01	504	574
sds(drive_sMILEPOSTROUTEML2200_1)	1.81	1.17	0.45	4.69	1.00	1968	1052
sds(drive_sMILEPOSTROUTEML2203_1)	1.00	1.01	0.03	3.64	1.00	2102	1051
sds(drive_sMILEPOSTROUTEML23_1)	0.85	0.40	0.31	1.87	1.00	792	1182
sds(drive_sMILEPOSTROUTEML2300_1)	0.60	0.41	0.10	1.64	1.00	951	888
sds(drive_sMILEPOSTROUTEML2302_1)	1.19	0.91	0.11	3.55	1.00	1348	927
sds(drive_sMILEPOSTROUTEML2303_1)	1.11	0.77	0.09	2.97	1.01	577	430
sds(drive_sMILEPOSTROUTEML24_1)	1.99	1.00	0.79	4.70	1.00	783	851
sds(drive_sMILEPOSTROUTEML25_1)	0.86	0.25	0.50	1.46	1.00	620	1071
sds(drive_sMILEPOSTROUTEML26_1)	0.53	0.44	0.04	1.65	1.00	794	697
sds(drive_sMILEPOSTROUTEML27_1)	1.04	0.96	0.04	3.64	1.00	837	731
sds(drive_sMILEPOSTROUTEML29_1)	0.89	0.55	0.26	2.20	1.00	996	764
sds(drive_sMILEPOSTROUTEML30_1)	0.36	0.28	0.04	1.08	1.01	546	725
sds(drive_sMILEPOSTROUTEML300_1)	0.29	0.38	0.01	1.34	1.00	782	950
sds(drive_sMILEPOSTROUTEML302_1)	0.39	0.35	0.02	1.32	1.00	697	1201
sds(drive_sMILEPOSTROUTEML303_1)	0.99	0.66	0.21	2.69	1.00	1100	911
sds(drive_sMILEPOSTROUTEML31_1)	0.42	0.32	0.04	1.21	1.00	575	600
sds(drive_sMILEPOSTROUTEML33_1)	1.82	0.92	0.62	4.17	1.01	600	417
sds(drive_sMILEPOSTROUTEML34_1)	0.54	0.46	0.13	1.64	1.00	318	624
sds(drive_sMILEPOSTROUTEML35_1)	2.32	2.72	0.39	8.99	1.01	396	219
sds(drive_sMILEPOSTROUTEML352_1)	0.56	0.54	0.02	1.81	1.00	945	1130
sds(drive_sMILEPOSTROUTEML36_1)	1.17	0.58	0.50	2.61	1.00	1173	1236
sds(drive_sMILEPOSTROUTEML37_1)	0.88	0.75	0.16	2.90	1.01	443	889
sds(drive_sMILEPOSTROUTEML374_1)	0.81	0.64	0.04	2.48	1.00	707	838
sds(drive_sMILEPOSTROUTEML39_1)	1.23	1.04	0.08	3.79	1.01	528	817
sds(drive_sMILEPOSTROUTEML40_1)	0.69	0.47	0.06	1.90	1.00	911	985
sds(drive_sMILEPOSTROUTEML401_1)	0.67	0.59	0.03	2.17	1.00	1234	1064
sds(drive_sMILEPOSTROUTEML42_1)	1.38	0.81	0.38	3.37	1.00	686	740
sds(drive_sMILEPOSTROUTEML43_1)	1.12	0.48	0.48	2.31	1.00	877	1340
sds(drive_sMILEPOSTROUTEML44_1)	0.87	0.65	0.08	2.61	1.00	820	721
sds(drive_sMILEPOSTROUTEML46_1)	0.29	0.31	0.01	1.14	1.00	852	1112
sds(drive_sMILEPOSTROUTEML48_1)	2.91	1.06	1.55	5.47	1.00	1058	324

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sds(drive_sMILEPOSTROUTEML502_1)      0.65      0.63     0.02     2.10 1.01     1274      574
sds(drive_sMILEPOSTROUTEML60_1)       1.70      0.93     0.53     3.94 1.00     1334     1355
sds(drive_sMILEPOSTROUTEML600_1)      0.77      0.75     0.04     2.81 1.00     1545     1194
sds(drive_sMILEPOSTROUTEML601_1)      0.89      0.57     0.21     2.34 1.01      734      805
sds(drive_sMILEPOSTROUTEML604_1)      0.62      0.62     0.02     2.30 1.00     1286     1122
sds(drive_sMILEPOSTROUTEML607_1)      1.00      0.56     0.24     2.48 1.01      808      563
sds(drive_sMILEPOSTROUTEML6792_1)     1.35      0.94     0.15     3.68 1.00     1058      605
sds(drive_sMILEPOSTROUTEML707_1)      0.92      0.58     0.24     2.47 1.00     1625     1546
sds(drive_sMILEPOSTROUTEML708_1)      0.81      0.59     0.13     2.27 1.01      567      222
sds(drive_sMILEPOSTROUTEML710_1)      0.36      0.40     0.01     1.45 1.00      966      895
sds(drive_sMILEPOSTROUTEML80_1)       0.59      0.16     0.36     0.96 1.01      502      995
sds(drive_sMILEPOSTROUTEML803_1)      0.62      0.62     0.02     2.20 1.00     1445     1162
sds(drive_sMILEPOSTROUTEML85_1)       0.35      0.18     0.05     0.80 1.01      356      191
sds(drive_sMILEPOSTROUTEML90_1)       0.74      0.35     0.18     1.57 1.01      470      510
sds(drive_sMILEPOSTROUTEML91_1)       1.34      1.13     0.06     4.06 1.00     1427     1019

Regression Coefficients:
                Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
chute_Intercept     7.90      0.16     7.61     8.22 1.00     1489     1545
drive_Intercept     0.52      0.01     0.50     0.54 1.00      708      371

Further Distributional Parameters:
      Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
sigma     4.40      0.07     4.26     4.54 1.00     2389     1660
beta      6.40      0.12     6.17     6.63 1.00     2070     1346

Draws were sampled using sample(hmc). For each parameter, Bulk_ESS
and Tail_ESS are effective sample size measures, and Rhat is the potential
scale reduction factor on split chains (at convergence, Rhat = 1).

Warning message:
There were 21 divergent transitions after warmup. Increasing adapt_delta above
0.8 may help.
See http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
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