THESIS

QUANTITATIVE ASSESSMENT OF FLOODPLAIN FUNCTIONALITY IN COLORADO USING AN INDEX OF INTEGRITY

Submitted by

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ABSTRACT

QUANTITATIVE ASSESSMENT OF FLOODPLAIN FUNCTIONALITY IN COLORADO USING AN INDEX OF INTEGRITY

Floodplain integrity can be defined as the ability of a floodplain to support essential geomorphic, hydrologic, and ecological functions that maintain biodiversity and ecosystem services. Humans alter floodplain functionality by changing the physical landscape of the floodplain or by altering river flow regimes and subsequent floodplain inundation dynamics. This research evaluates floodplain integrity by assessing the prevalence of anthropogenic modifications to hydrology and landscape. Specifically, the objectives of this research are to: 1) develop a methodology to assess floodplain integrity using geospatial datasets available for large spatial scales; and 2) use the methodology to evaluate spatial patterns of floodplain integrity in the state of Colorado. To accomplish these objectives, I evaluated the critical floodplain functions of attenuating floods, storing groundwater, regulating sediment, providing habitat, and regulating organics and solutes. At present, this work is the first to quantify the integrity of specific floodplain functions instead of measuring floodplain health solely by ecological integrity. I applied the index of floodplain integrity methodology in the state of Colorado to analyze the integrity of each of the five floodplain functions and the aggregated overall integrity. In Colorado, overall floodplain integrity decreased as stream order increased above third order streams. Floodplain integrity was also lower in floodplains that intersected urban areas than those that did not, which indicates the index of floodplain integrity captured the adverse relationship between development and floodplain health established in literature. By quantifying anthropogenic reductions to floodplain functionality at broad spatial scales, the index of floodplain integrity can help target restoration efforts towards the most affected functions and areas.

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1 Introduction

1.1 Floodplain functions

Floodplains are unique and vital ecosystems. They support unparalleled levels of biodiversity (Tockner and Stanford, 2002; Ward et al., 1999), are among the most productive landscape types (Tockner and Stanford, 2002), and are second only to estuaries in terms of global value of ecosystem services (Costanza et al., 1997). The characteristic intermittent wetting and drying of floodplains allows them to serve a multitude of purposes to support a healthy ecosystem. The most vital floodplain functions can be summarized as:

1) Flood reduction: Floodplains help attenuate floods by storing water and slowing peak flows (Burt, 1997; Helton et al., 2014).
2) Groundwater storage: Floodplains greatly increase hydraulic residence time and groundwater recharge by increasing vertical hydraulic connectivity (Brunke and Gonser, 1997; Helton et al., 2014; Stanford and Ward, 1993).
3) Sediment regulation: Floodplains provide a buffer between the zones of sediment creation and transport, serving as either a sediment source or a sink depending on the sediment and flow regime present (Fryirs, 2013; Fryirs et al., 2007; Nanson and Croke, 1992; Wohl et al., 2015).
4) Organics and solutes regulation: Floodplain heterogeneity and intermittent wetting makes them well suited to retaining and transforming various forms of carbon and nutrients (Brunke and Gonser, 1997; Noe and Hupp, 2009; Sutfin et al., 2016; Wollheim et al., 2014).
5) Habitat provision: Floodplains support high biodiversity and provide habitat crucial to the life cycle of many aquatic species due to their heterogeneity and high productivity (Brunke and Gonser, 1997; Junk et al., 1989; Tockner and Stanford, 2002; Ward et al., 1999).

Despite the variety of important functions they perform, floodplains are among the most threatened ecosystems and are disappearing at a faster rate than other landscapes due to human alteration (Tockner and Stanford, 2002). In a summary of the current state and future of floodplains, Tockner and Stanford arrived at the alarming conclusion that if there is any hope for sustaining floodplains long term, “highly enlightened management and restoration efforts” are crucial. A useful first step in improving or protecting floodplains using management and restoration efforts includes assessing overall floodplain health or integrity.

1.2 Integrity of environmental systems

The concept of integrity in an environmental context was first discussed by Leopold in his landmark 1949 essay that introduced his Golden Rule of Ecology that, “A thing is right when it tends to preserve the integrity, stability, and beauty of the biotic community. It is wrong otherwise.” (Leopold, 1949). In the following decades, various works explored and clarified the definitions of ecological and biological integrity and their use in environmental management (Angermeier and Karr, 1994; Karr, 1996, 1992; Karr and Dudley, 1981). Importantly, these explorations clarified that reductions to integrity were defined explicitly to be caused by human alterations as opposed to natural disturbances (Karr, 1981).

Further work applied the concept of environmental integrity to guide watershed management perspectives (Novotny et al., 2005; USEPA, 2012, 1998). The definition of high watershed integrity ranged from a watershed that sustains ecosystem services for humans (USEPA, 1998) to a watershed completely free of human influence (Novotny et al., 2005; USEPA, 2012). Flotemersch et al. (2016) attempted to resolve this ambiguity and create an operable definition of environmental integrity as “the capacity of a system (and its sub-components) to support and maintain the full range of ecosystem processes and functions essential to the long-term sustainability of its it is [*sic*] diversity and natural resources” (Flotemersch et al., 2016).

The definition of integrity proposed by Flotemersch et al. (2016) can be applied to ecological units besides watersheds, such as floodplains. At present, studies of integrity in floodplains are predominantly focused on ecological integrity in the floodplains rather than assessing integrity of the floodplains themselves (Chovanec et al., 2003; Chovanec and Waringer, 2001; Petts, 1996). The key difference between assessing ecologic integrity in floodplains and assessing floodplain integrity is that ecologic integrity focuses solely on habitat quality, therefore providing little or no information about the other four functions of healthy floodplains listed in Section 1.1. In contrast, Konrad (2015) performed a holistic assessment of floodplain functions for major rivers in the Puget Sound. Though not explicitly stated as a study of floodplain integrity, this assessment of the anthropogenic changes to a variety of floodplain functions fits the definition of integrity proposed by Flotemersch et al. (2016).

1.3 Quantifying floodplain integrity

Although a consistent definition of floodplain integrity is a necessary first step, the usefulness of the concept of floodplain integrity from a management perspective is in being able to measure it. Konrad (2015) provides an example of a method for assessing floodplain integrity at a broad spatial scale using GIS analysis of spatial data. However, one limitation of this study is that the resulting evaluations are categorical; for each floodplain function, the floodplain in question is assigned to a category. The categories provide specific information about the functions but have no hierarchy of integrity. This method of categorical assessment provides substantial information about floodplain condition at a given location but limits comparisons and analysis of spatial trends. Brinson (1996) emphasizes the importance of numerical assessments while proposing a method to evaluate wetland functionality, noting that identifying which functions are impacted and by how much moves restoration efforts from “fuzzy generalities” to specific goals.

Congruent to this focus on quantifiable evaluations, Flotemersch et al. (2016) and Thornbrugh et al. (2018) develop and then employ a methodology to quantitatively assess watershed integrity, which I use as the basis for this methodology to quantify floodplain integrity presented in this paper. Remarking that unaltered reference watersheds are practically non-existent (Stoddard et al., 2006), Flotemersch et al. (2016) instead propose studying the presence of anthropogenic stressors to measure changes to watershed function. Thornbrugh et al. (2018) implemented this methodology to assess watershed integrity for the continental United States using broadly available datasets. The result was an Index of Watershed Integrity (IWI) and Index of Catchment Integrity (ICI) ranging from zero to one (lowest to highest integrity) for all catchments and watersheds associated with the National Hydrography Dataset Version 2 stream segments. Although the ICI and IWI were calculated for six watershed functions and an aggregated overall value, Thornbrugh et al. (2018) conclude that the index representing hydrologic alteration could be used to represent overall watershed integrity more efficiently and with minimal loss of information compared to calculating and combining all six functional metrics.

This study builds off the advances made in both the qualitative assessment of floodplains in the Puget Sound region of Konrad (2015) and the quantitative assessment of watershed integrity in Thornbrugh et al. (2018) by developing a novel methodology to quantitatively assess floodplain integrity and applying the methodology to floodplains in the state of Colorado.

1.4 Index of floodplain integrity

For the purpose of this study, floodplain integrity is defined as the ability of a floodplain to support essential geomorphic, hydrologic, and ecological functions that maintain biodiversity and ecosystem services provided to society. Similar to Thornbrugh et al. (2018), I aim to address the limitations of inefficient small-scale field studies and the lack of a truly unaltered reference environment by using available datasets to assess the level of alteration to floodplains. However, as floodplains are unique hydrogeomorphic features, the functions they provide and the human alterations that inhibit these functions are unique from those of entire watersheds. In particular, floodplain functionality is dependent not only on the physical landscape of the floodplain, but also driven by the frequency and duration of overbank flooding (Opperman et al., 2010). Because of the tight link between floodplain inundation and floodplain function, I chose to explicitly include human alterations to river hydrology, which were absent from Thornbrugh et al. (2018), as a stressor variable in the assessment of floodplain integrity.

The objectives of this research are to: 1) develop a methodology to assess floodplain integrity using geospatial datasets available for large spatial scales; and 2) use the methodology to evaluate spatial patterns of floodplain integrity in the state of Colorado. Colorado is large enough to ensure my proposed approach can be used for a large spatial extent, while still providing a refined spatial extent for iterating on the methodology. Additionally, Colorado contains varied geomorphology, climate, hydrology, and levels of human alteration, which ensures a robust evaluation of the methodology. Through quantifying the abundance of anthropogenic alterations to floodplains in the state of Colorado, this research produces and analyzes an index of floodplain integrity (IFI) for each of the five floodplain functions and an aggregated overall IFI.

2 Links between floodplain functions and human stressors

In order to quantify the effects of humans on floodplains, I first identified specific anthropogenic alterations that reduce floodplain functionality. As the intent of this research is to measure anthropogenic disturbance, I did not consider the impact of natural disturbances, such as fires or landslides, on floodplain functions. I used the literature highlighted below to identify relevant stressors and their effect for the five floodplain functions, with my findings summarized in Figure 1. I later used these identified stressors to choose relevant datasets, which are discussed in Section 3.2 and illustrated in Table 3.

2.1 Flood reduction stressors

Floodplains' potential to reduce peak flows and provide transient surface water storage is stressed by human developments in the floodplain that lower the floodplain storage capacity and therefore increase flood stage for the same volume of water (Konrad, 2003; Larson and Plasencia, 2001; Wheater and Evans, 2009). Levees are a particularly important stressor, as they can completely cut off connection with the floodplain (Criss and Shock, 2001; Tobin, 1995; Wheater and Evans, 2009). Roads and railroads also hinder flood attenuation by being a barrier that isolates segments of the floodplain (Beevers et al., 2012; Kumar et al., 2014; Tarolli and Sofia, 2016), intercepting and diverting subsurface flow (Wemple and Jones, 2003), or increasing runoff by collecting and channelizing surface flow, which increases flood peaks (Tarolli and Sofia, 2016). Flood attenuation is also sensitive to changes in land cover, as vegetation helps to slow and store floodwater (Nicholson et al., 2012; Sholtes and Doyle, 2011; Zell et al., 2015) and urbanization increases conveyance and therefore flood peaks (Wheater and Evans, 2009).

2.2 Groundwater storage stressors

The ability of floodplains to store and regulate groundwater is primarily stressed by reductions in vertical connectivity. These reductions can be driven by increased area of impermeable surface in floodplains, which reduces infiltration (Brunke and Gonser, 1997; Wheater and Evans, 2009). Infiltration can also be limited by channelization of overland flow as this decreases the contact time and area by hastening the movement of surface flows from the floodplain to the river (Brunke and Gonser, 1997; Hancock, 2002; Wheater and Evans, 2009). Colmation, or clogging of interstitial spaces in alluvial sediments, also reduces infiltration in

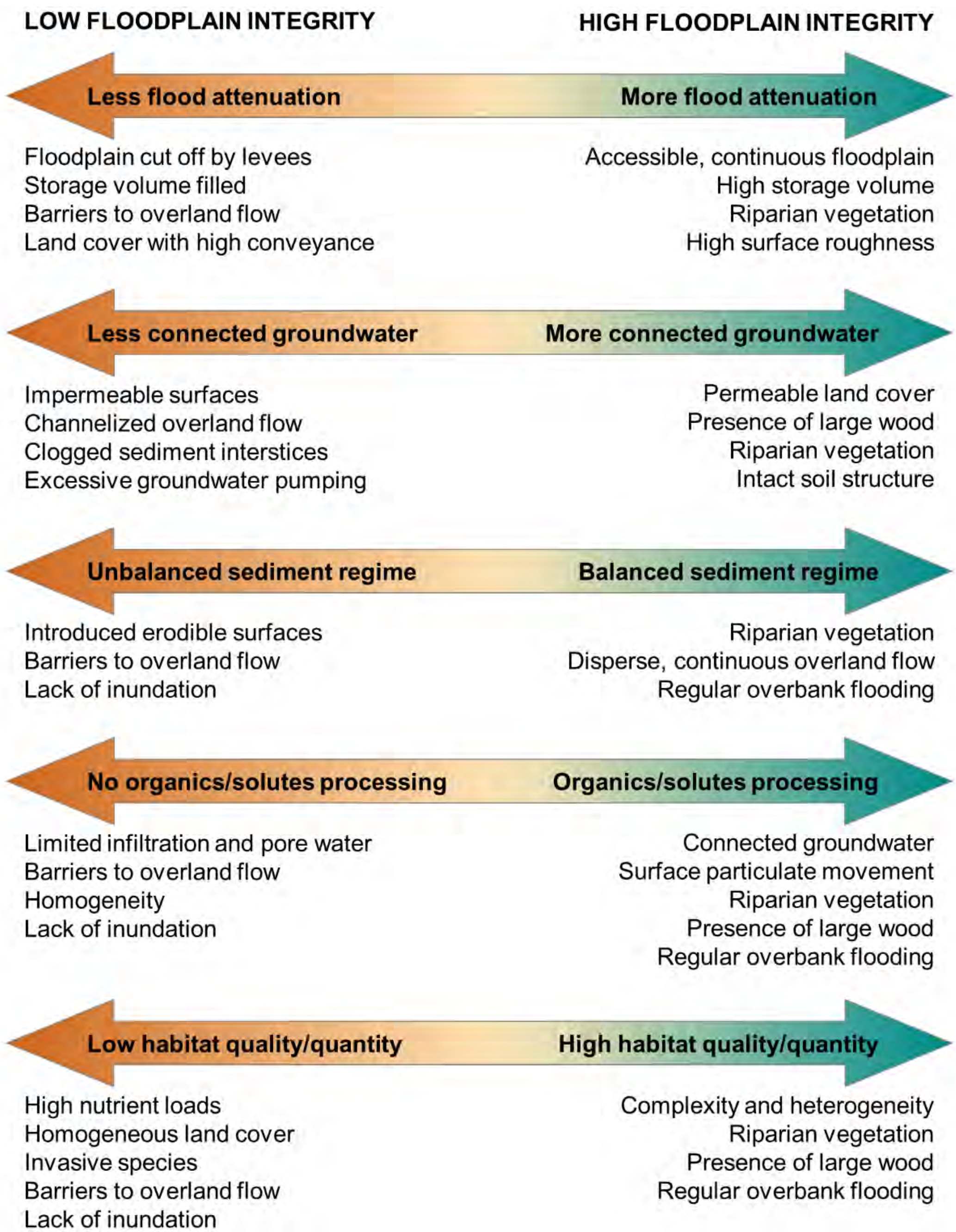

Figure 1. Conceptual diagram of floodplain functional integrity and the variables that change each function.

floodplains. Colmation can be caused by increased fine sediment loading, increased algal growth, and degradation of soil structure, which are often responses to changes in land cover (Brunke and Gonser, 1997; Hancock, 2002; Wheater and Evans, 2009). Excessive pumping of groundwater can also contribute to colmation (Brunke and Gonser, 1997). In the short term, pumping of groundwater can lower the water table and provide increased groundwater storage. However, in the long term, lowering the groundwater table endangers riparian vegetation, which harms soil structure and increases erosion and therefore reduces groundwater connectivity (Brunke and Gonser, 1997). Finally, vertical connectivity can be enhanced by riparian vegetation, large wood, and beaver dams, which serve to improve soil structure, increase ponding, and increase time for infiltration (Boulton, 2007; Hancock, 2002; Harper et al., 1999; Wheater and Evans, 2009).

2.3 Sediment regulation stressors

Floodplains' ability to serve as sediment buffer zones is dependent on the floodplain landscape and floodplain inundation dynamics. Unaltered floodplains help to moderate the sediment regime by switching roles between being a sediment source or sediment sink, but anthropogenic land cover change can shift this balance (Lecce, 1997; Wohl et al., 2015). In particular, agriculture in floodplains has increased sediment supply and erodibility, causing floodplains to be a greater sediment source (Knox, 2006; Walling and Fang, 2003; Wheater and Evans, 2009). Removal of riparian vegetation also shifts the role of floodplains in the sediment regime because riparian vegetation helps filter suspended sediment and reduce sediment yield to rivers (Brunke and Gonser, 1997; Wheater and Evans, 2009), and reductions in riparian vegetation make flows much more effective at mobilizing sediment (Fryirs, 2013). Sediment connectivity and residence time are also affected by roads and railroads, which can increase sediment production in floodplains by intercepting and channelizing surface flows, which increases their erosive power (Persichillo et al., 2018; Tarolli and Sofia, 2016). Additionally, the natural cycle of sediment deposition and erosion in floodplains is disproportionately dependent on large overbank flows (Florsheim and Mount, 2003; Wohl et al., 2015), and therefore is severely limited by reductions in the magnitude or frequency of peak flows (Fryirs, 2013; Nanson, 1986).

2.4 Organics and solutes regulation stressors

The storage of organics and the chemical processing that occurs in floodplains are also dependent on both the landscape and the inundation of the floodplain. Regular overbank flooding is beneficial for accumulation of organic matter and enhancing denitrification (Craig et al., 2008; Sgouridis et al., 2011; Tockner et al., 1999), and thus hydrologic alteration can change the processing of organics and solutes in floodplains. Connectivity of groundwater is also important for nutrient processing and filtration (Brunke and Gonser, 1997; Burt, 1997; Stanford and Ward, 1993) therefore impermeable areas that limit vertical connectivity in floodplains reduce floodplain solute regulation. Reductions in lateral overland connectivity are also a stressor, as connected surface flow is responsible for particulate movement (Tockner et al., 1999). Vegetation and large wood contribute to retention of organic matter and nutrient loads and carbon storage in floodplains (Craig et al., 2008; Hanberry et al., 2015; Harper et al., 1999; Pinay and Decamps, 1988; Stanford and Ward, 1993; Sutfin et al., 2016). Floodplains can also be a significant source of organics and solutes due to autochthonous production (Junk et al., 1989; Roach et al., 2014). Consequently, the loss of riparian vegetation and associated loss of complexity can reduce mediation and change the production of organics and solutes in floodplains.

2.5 Habitat stressors

Many anthropogenic modifications to floodplains degrade habitat and result in loss of biodiversity. For instance, changes in land use towards urbanization and agriculture reduce biodiversity and increase nutrient pollution (Harper et al., 1999; Tockner et al., 1999). Floodplain habitat is also highly vulnerable to species invasion, which can harm fitness of native species and reduce aquatic biodiversity (Tockner et al., 1999). Lateral connectivity of floodplain habitat is an important contributor to floodplain heterogeneity (Ward and Stanford, 1995), and therefore development that blocks the movement of water and aquatic species in the floodplain reduces habitat area and quality (Beevers et al., 2012; King et al., 2003). Additionally, loss of trees and large wood in floodplains leads to less complex and diverse habitat and reduces channel migration, producing a cyclic effect that can lead to further loss of native riparian vegetation (Collins et al., 2012; Harper et al., 1999). Finally, floodplain habitat can be detrimentally impacted by hydrologic alteration, as regular overbank flows are vital to maintain biodiversity, habitat heterogeneity, and ecosystem dynamism (Amoros and Bornette, 2002; Brunke and Gonser, 1997; Galat et al., 1998; Harper et al., 1999; Higgisson et al., 2019; Junk et al., 1989; Tockner et al., 1999; Ward et al., 1999).

3 Methods

In order to assess floodplain integrity, I first identified datasets that represent the anthropogenic stressors to floodplain functions described in Section 2. Next, I calculated the prevalence of these stressors in discretized floodplain units. From the relative densities of these stressors in the floodplain, I calculated an IFI for each of the five floodplain functions. Then, I combined these functional IFI values to make an overall IFI metric. The functional and overall IFI values range from zero to one, representing floodplains where functionality is most to least altered, respectively. This process is represented graphically in Figure 2 and each step is described in detail in the following sections, with a sample calculation provided in Appendix A.

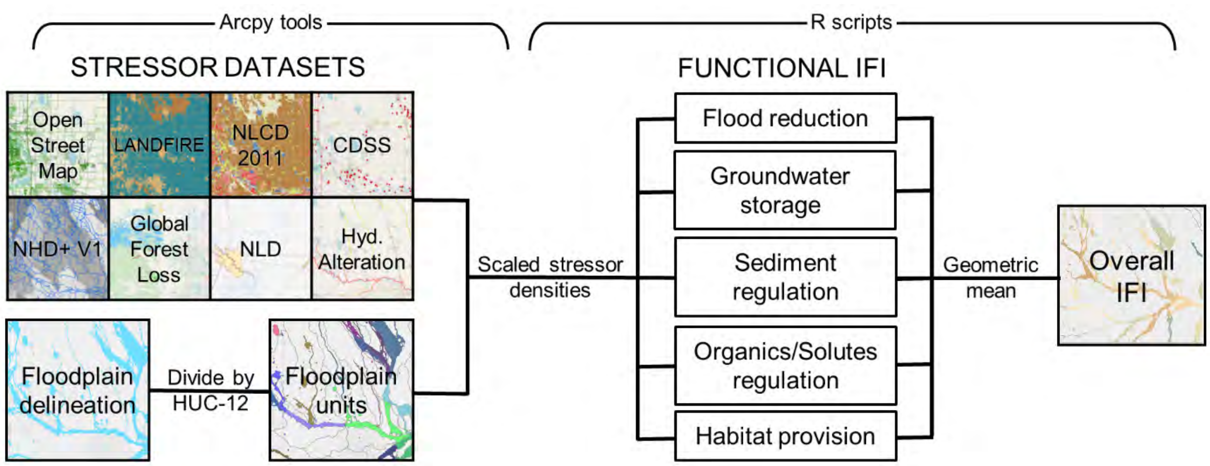

Figure 2. Overview of IFI methodology.

3.1 Discretization of floodplain units

Assessing the integrity of floodplains across Colorado requires a floodplain delineation for the entire state. Floodplain boundaries used in the project were adapted from results of flood hazard mapping performed for the conterminous United States at a 30 m resolution using a 2D hydrodynamic model and regionalized flood frequency estimates (Wing et al., 2017). The floodplain delineation used in this research is associated with the 100-year flood in an "undefended" (without levees) condition.

From the floodplain delineation for the entire US, I extracted a floodplain shapefile for the state of Colorado. I performed minor cleaning of the delineated floodplains by filling gaps and removing disconnected islands in the shapefile that were smaller than 3 raster grid cells (< 2,700 m^2). This minor cleaning changed the overall area of the delineated floodplain in Colorado from 14,202 km^2 to 14,214 km^2 (+0.0008 %).

To create smaller floodplain units to compare across the state, I divided floodplains along the boundaries of sub-watersheds delineated by 12-digit hydrologic unit codes (HUC-12s) from the Watershed Boundary Dataset (Seaber, 1987). This resulted in 3,025 floodplain units in the state with an average of 4.70 km^2 per floodplain unit (Figure 3).

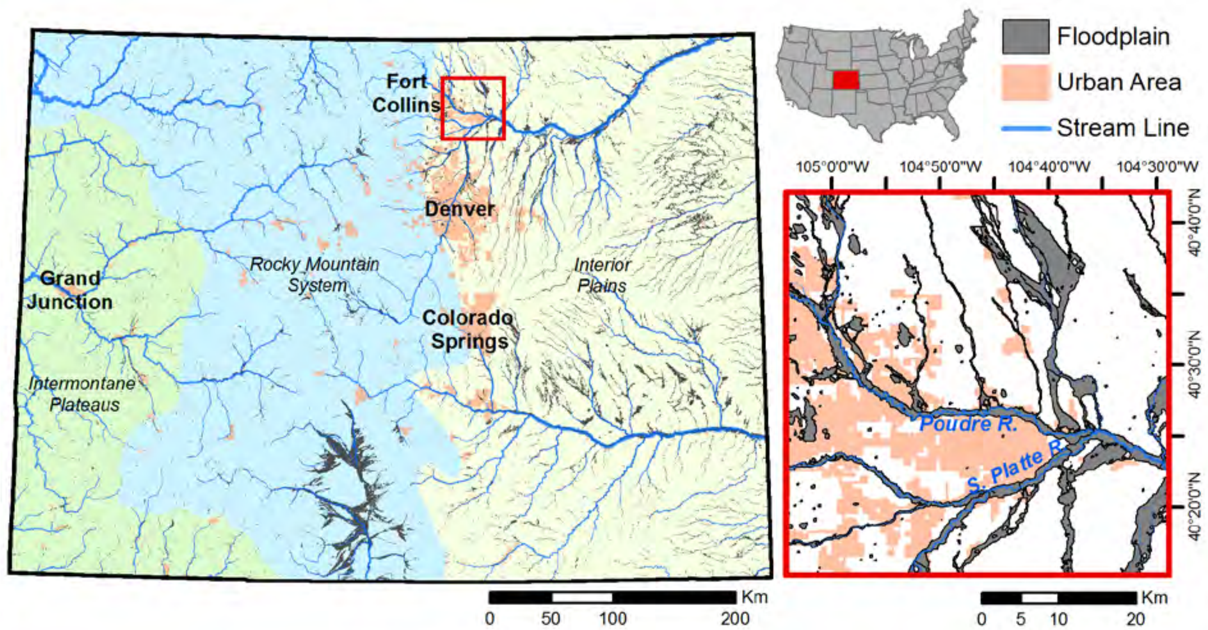

Figure 3. Floodplain study location map. The state of Colorado (red on US map) is shown with fourth order and larger rivers (blue), census-designated and incorporated areas (orange), physiographic regions (green, blue, and yellow shading), and floodplain areas (grey). The red inset map shows a close-up view of the floodplain units divided by HUC-12 boundary.

I associated each floodplain unit with a stream order using the National Hydrography Dataset Version 1 (NHDPlus V1) streamlines (McKay et al., 2010). Each floodplain unit was assigned the maximum stream order in the associated HUC-12 based on the assumption that the majority of the floodplain area will be preferentially associated with the largest streams in a given

HUC-12. Of the HUC-12 sub-basins used to divide the floodplain, 100 HUC-12s do not contain an NHDPlus V1 streamline with a reported stream order, and therefore there is no stream order associated with 100 floodplain units. Floodplains were also associated with a physiographic division (Fenneman, 1917) based on the region in which the majority of the floodplain area was contained. Summaries of floodplain area by stream order and physiographic region can be found in Table 1 and Table 2, respectively.

Table 1. Floodplain area by stream order.

Stream Order	Floodplain Area (km^2)
1	486
2	1,507
3	2,817
4	3,788
5	2,284
6	932
7	1,136
8	5
N/A	1,258
Total	14,214

Table 2. Floodplain area by physiographic region.

Physiographic Division	Floodplain Area (km^2)
Intermontane Plateaus	1,063
Rocky Mountain System	4,495
Interior Plains	8,656
Total	14,214

3.2 Identification of stressor datasets

Once I determined the relevant stressors for each floodplain function, I identified datasets that could be used to measure the amount of each stressor across Colorado floodplains. I selected datasets based on the following criteria: 1) information contained in the dataset was available for the entire state; 2) the datasets were the same or finer spatial scale than the floodplain delineation; and 3) the datasets were publicly available or soon to be publicly available. My intention in focusing on publicly available datasets was to create a methodology that could easily be replicated and updated without needing to contact individuals or organizations for access to data.

The datasets I selected vary in their representativeness of the stressors. In some cases, datasets that directly measured the stressor were available, such as the National Landcover Database (NLCD) percent impervious surface raster data to quantify impervious surface coverage. For other stressors, I was unable to identify a large-scale measurement and reporting effort, so I instead used proxy indicators of the stressor for which data were available. For instance, since measurements of groundwater depletion in Colorado are not currently available at the scale and coverage required, I estimated this stressor with the density of groundwater wells in the floodplain. The datasets used to represent each stressor and important characteristics of the datasets are shown in Table 3. Note that the same stressor may be represented by a different dataset for a different function, or that the same dataset may be used to represent several stressors. These links between the datasets and the stressors were informed by the function-specific review presented in Section 2.

One unique dataset used in this study is an estimate of the magnitude of change for a variety of indicators of hydrologic alteration for NHDPlus V1 stream lines. This dataset was created following the method described in McManamay et al. (2017) and extended to additional hydrologic alteration metrics (see Olden and Poff (2003) for definitions of the indicators of hydrologic alteration). To create this dataset, hydrologic alterations at USGS gages across the U.S. were calculated using modeled estimates of natural flows from USGS reference gage sites (Falcone, 2017). Hydrologic alteration was then extrapolated from gages to stream reaches using random forest models based on fifty-two water cycle related variables. The hydrologic alteration dataset was developed in collaboration with Ryan McManamay at Oak Ridge National Laboratory. This novel data-driven modeling of hydrologic alteration represents a notable advancement over representing hydrologic alteration using proxies such as the presence of dams and irrigation canals. This dataset provides estimates for several relevant indicators of hydrologic alteration that represent changes in the magnitude, duration, frequency, and timing of flows of various return intervals. However, because all of the relevant indicators were highly correlated (see Appendix A), I chose to use a single indicator to represent all types of change to hydrology. I selected alterations to M_H20, or mean annual maximum flow divided by catchment area, as the metric to represent hydrologic alteration, as its physical meaning is simple to understand and the mean annual maximum flow is likely to activate the floodplain. Although this hydrologic alteration dataset is not currently available to the public, I chose to include the dataset in this investigation as the data will be published and available in the near future.

3.3 Calculation of stressor density

After I identified a dataset to represent each stressor, I was able to quantify the level of each stressor within the floodplain. The method I used to compute the stressor density was dependent on the data type. Polygon, polyline, and point type stressor datasets all represented binary stressor presence or absence, such that prevalence of the shape features indicated the prevalence of the stressor. As such, I calculated the stressor level as the density of the polygons, polylines, and points in the floodplain unit in km^2/km^2, km/km^2, and $count/km^2$, respectively. For the forest cover loss dataset, the percentage of cells in the floodplain that reported forest loss events between 2000 and 2018 was computed. Prevalence of developed area was considered the percentage of cells in the floodplain reported as high, medium, or low intensity development (NLCD classes 21-24). I computed the level of agriculture as the percentage of cells in the floodplain reported as pasture/hay or cultivated crops (NLCD classes 81 and 82). To quantify impervious surface, I averaged the percent imperviousness values reported for each 30 m cell for all cells in the floodplain. I computed the percentage of non-native introduced vegetation as the percentage of cells in the LANDFIRE Existing Vegetation Type raster reported as groups 701-709, 711, and 731, which represent various types of invasive, non-agricultural plant species. The hydrologic alteration dataset reports the probability of change to the indicator M_H20, or specific mean annual maximum flow, for each connected NHDPlus V1 segment. To aggregate these

Table 3. Summary of datasets used to represent floodplain function stressor.

Floodplain function	Stressor	Dataset	Data attributes
Flood reduction	Reduced storage volume	Buildings[1]	Polygon, July 17, 2018 version
	Floodplain disconnection	Leveed area[2]	Polygon, April 2015
	Overland flow interception	Roads and Railroads[1]	Polyline, July 17, 2018 version
	Land cover change	Forest cover loss events[3]	Raster, 30m resolution, loss 2000 – 2018
		Developed area[4]	Raster, 30m resolution, 2011 version
Groundwater storage	Impermeable surface	Percent imperviousness[4]	Raster, 30m resolution, 2011 version
	Channelized overland flow	Ditches and canals[5]	Polyline, 1:100,000 scale, 2006 release
	Colmation	Agricultural area[4]	Raster, 30m resolution, 2011 version
	Loss of wood and vegetation	Forest cover loss events[3]	Raster, 30m resolution, loss 2000 – 2018
	Lowered water table	Groundwater wells[6]	Points, October 2018
Sediment regulation	Land cover change	Agricultural area[4]	Raster, 30m resolution, 2011 version
	Loss of wood and vegetation	Forest cover loss events[3]	Raster, 30m resolution, loss 2000 – 2018
	Overland flow interception	Roads and Railroads[1]	Polyline, July 17, 2018 version
	Hydrologic alteration	Probability of change in M_H20[7]	Data for NHD+ V1 polylines, 2018 hydrology data
Organics and solutes regulation	Hydrologic alteration	Probability of change in M_H20[7]	Data for NHD+ V1 polylines, 2018 hydrology data
	Vertical connectivity	Percent imperviousness[4]	Raster, 30m resolution, 2011 version
	Overland flow interception	Roads and Railroads[1]	Polyline, July 17, 2018 version
	Loss of wood and vegetation	Forest cover loss events[3]	Raster, 30m resolution, loss 2000 – 2018
Habitat provision	Land cover change	Developed area[4]	Raster, 30m resolution, 2011 version
		Agricultural area[4]	Raster, 30m resolution, 2011 version
	Loss of wood and vegetation	Forest cover loss events[3]	Raster, 30m resolution, loss 2000 – 2018
	Species invasion	Non-native introduced vegetation[8]	Raster, 30m resolution, 2014 release
	Overland flow interception	Roads and Railroads[1]	Polyline, July 17, 2018 version
	Hydrologic alteration	Probability of change in M_H20[7]	Data for NHD+ V1 polylines, 2018 hydrology data

1. OpenStreetMap Contributors, 2018
2. National Levee Database; USACE, 2015
3. Global Forest Loss Dataset; Hansen et al., 2013
4. National Landcover Database; Homer et al., 2012
5. National Hydrography Dataset, Version 1; McKay et al., 2010
6. Colorado Decision Support System; CWCB/DNR, 2018
7. Hydrologic Alteration Data; McManamay et al., 2017 and personal communication
8. LANDFIRE Existing Vegetation Type; Rollins, 2009

stream segment values to one number for each floodplain unit, I averaged the values for the streamlines of the maximum order in the floodplain unit. This aggregation method is based on the assumption that the floodplain area is preferentially associated with higher order streams. Refer to Appendix A for an investigation of alternate streamline-to-floodplain hydrologic alteration value aggregation methods. I computed all stressor densities in the floodplain units using ArcGIS tools written in Python (see Appendix B).

3.4 Stressor rescaling

Using the methods described in Section 3.3, I calculated the quantity of each stressor in each floodplain unit. Stressors datasets that were raster or polygon type measured stressor density in area, and therefore have a theoretical maximum value of one. However, polyline and point type datasets have no theoretical maximum. Additionally, most of the stressor area densities observed in Colorado are much lower than one as the likelihood of a single stressor occupying the entire floodplain area is very low. Accordingly, I rescaled quantities of each stressor from zero to one, with a zero value indicating absence of stressor in the floodplain and value of one being the 90th percentile of the stressor levels in the floodplain observed in Colorado. All stressor levels over the 90th percentile were assigned a value of one. However, for the two datasets for which 90 percent or greater of the floodplain units still had no stressor present (leveed area and wells), a value of one instead corresponded to the maximum observed value.

I performed this rescaling for two main reasons. First, it provided a more consistent method to quantify the prevalence of stressors on a zero to one scale when using several different data types (i.e., areas, lines, and points). Secondly, it provided much more spread amongst the observed levels of the stressors compared to unscaled stressor densities. As the purpose of the IFI is to provide a comparison between floodplains across the state, this increased spread makes comparisons between floodplain units more meaningful, rather than a comparison to a theoretical worst case scenario. One limitation of this rescaling of the datasets is that the scaling now depends on the observed data, which makes comparisons between separate computations of the

IFI more difficult. Plots of the rescaled data and a more in-depth discussion of the scaling rationale can be found in Appendix A.

3.5 Calculation of IFI for functions

Using the scaled quantities of each stressor in each floodplain unit, I calculated the IFI values for the five floodplain functions. First, I performed a Pearson correlation analysis for the scaled stressor data for the floodplain units (see Appendix A). For any two stressor datasets with correlation coefficients greater than 0.7, only one of the stressors was included in the calculation of each function to avoid over-weighting one stressor type. With the remaining stressor datasets, I calculated the function IFI for each of the five functions as

$$IFI_{i,k} = 1 - \frac{\sum_{j=1}^{n_{j,k}} S_{i,j}}{n_{j,k}}$$

where $IFI_{i,k}$ is the integrity of the ith floodplain unit for the kth function; $S_{i,j}$ is the scaled stressor value for the jth stressor in the ith floodplain unit; and $n_{j.k}$ is the number of stressors, j, that impact floodplain function k. This function assumes a negative linear response to the abundance of stressors where higher values of scaled stressors in the floodplain equate to lower function IFI and vice versa. It also implies an equal weighting of all stressors that contribute to a given function. The assumptions of equal weighting and negative linear response to stressors are necessary simplifications due to the current lack of understanding of the complex functional responses in floodplains. Weighting and non-linear relationships could easily be incorporated into this methodology at this step should future research clarify the expected changes in functionality due to floodplain modifications.

3.6 Calculation of overall IFI

The overall IFI for each floodplain unit was calculated as the geometric mean of the five function IFI values, such that:

$$IFI_i = \left(\prod_{k=1}^{5} IFI_{i,k} \right)^{\frac{1}{5}}$$

where IFI_i is the overall index of integrity for the ith floodplain unit; and $IFI_{i,k}$ is the index of integrity for the kth function in the ith floodplain unit. I chose a geometric mean because each floodplain function is considered critical to floodplain function. Accordingly, if one function is evaluated at zero integrity, the overall integrity of the floodplain unit is also zero. The geometric average has previously been shown to be most appropriate for combining several essential and non-substitutable metrics into one index (Sandoval-Solis et al., 2011).

After computing the functional and overall IFI, I summarized the results based on spatial attributes. These attributes included the physiographic region and stream order of the floodplain (as described in Section 3.1), and also whether or not the floodplain unit intersected the TIGER2010 City Boundaries shapefile, which includes incorporated places and census designated places (*2010 TIGER/Line Shapefiles*, 2011).

3.7 Comparison to index of catchment integrity and wetland density

The overall IFI values were compared to the Index of Catchment Integrity (ICI) values computed in Thornbrugh et al., 2018. To allow a one-to-one comparison, I calculated the mean ICI of the catchments that intersected each floodplain unit. This produced a single ICI value for each floodplain unit.

Additionally, I compared the overall IFI values to the density of wetlands in the floodplains. Wetlands were considered to be areas of the classes “Freshwater Emergent Wetland” and “Freshwater Forested/Shrub Wetland” from the National Wetland Inventory (USFWS, 2018). The justification behind comparing IFI to wetland density is that wetlands are more likely to be supported in floodplains that have little human alteration as compared to floodplains that are highly modified.

4 Results

Using the HUC-12 identification number, the computed function and overall IFI values were mapped to the floodplain across the state of Colorado (see Appendix C for a full map of overall IFI in Colorado and Appendix A for a map of Colorado with HUC-12s colored by the overall IFI of the floodplain they contain). Figure 4 shows the distribution of the computed IFI values by area of floodplain for each of the five floodplain functions and the overall IFI. IFI values for all functions and overall are left skewed, with the highest skew occurring for flood reduction and groundwater storage. Statistics of the computed overall and function IFI values are summarized in Table 4. The functional IFI values are generally highly correlated, with correlation coefficients ranging from 0.65 to 0.89 (see Appendix A).

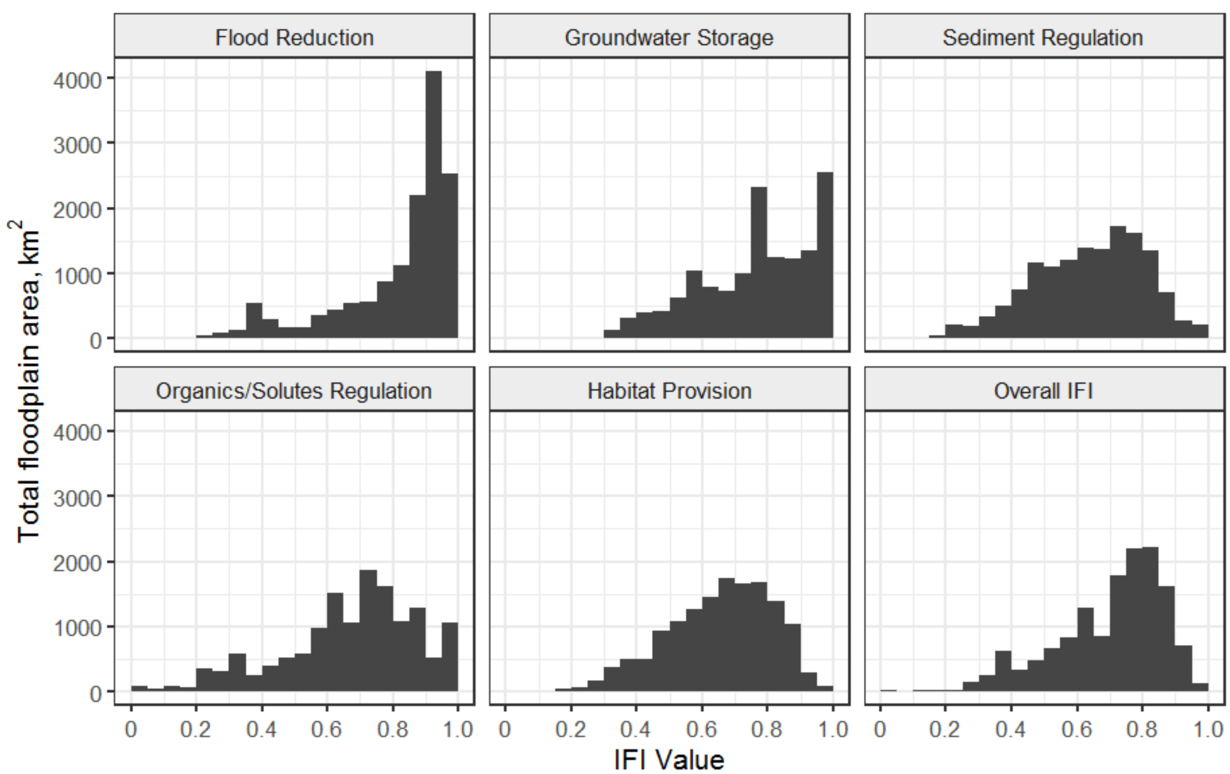

Figure 4. Prevalence of IFI value by total floodplain area for each of the five floodplain functions and the aggregated overalll IFI. Note that all functions and overall IFI show a left skew.

Table 4. Summary statistics of computed IFI for overall integrity and floodplain functional integrity.

	Overall IFI	Flood reduction	Groundwater storage	Sediment regulation	Organics/Solutes regulation	Habitat provision
Minimum	0.00	0.20	0.25	0.05	0.00	0.16
Median	0.76	0.89	0.85	0.68	0.73	0.71
Mean	0.73	0.82	0.83	0.67	0.68	0.69
Maximum	1.00	1.00	1.00	1.00	1.00	1.00
Std. dev.	0.16	0.18	0.15	0.17	0.20	0.15

Figure 5 shows a sample of the mapped IFI results at a 1:1,000,000 scale for the region of Colorado shown in the red box on Figure 3. In Figure 5, there are visible gradients in integrity present. Similar spatial patterns are present for the overall IFI and functional IFI values, although magnitudes of IFI differ.

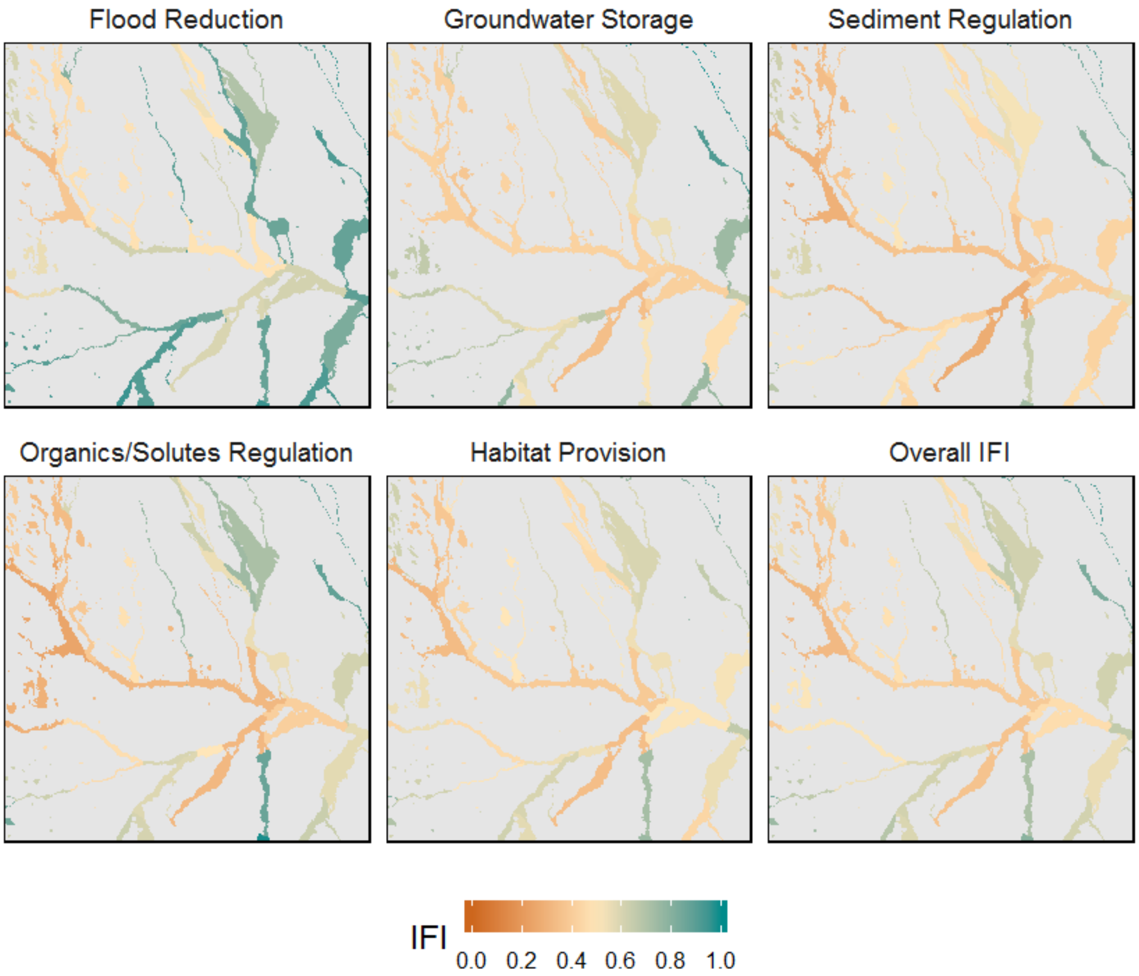

Figure 5. Close up of mapped IFI values for each of the five floodplain functions and overall IFI. The region of Colorado shown in this figure is the same close-up region shown in Figure 3. Gradients of color representing gradients in floodplain integrity are present.

IFI values were analyzed by physiographic region, urban versus rural area, and stream order, with results shown in Figure 6. Using Tukey Honestly Significant Difference (HSD) test (Tukey, 1953), floodplains in the Interior Plains region (median = 0.81, mean = 0.78) have a significantly different average IFI (p < 0.0001) than the Intermontane Plateau (median = 0.72, mean = 0.70) or Rocky Mountain System regions (median = 0.71, mean = 0.69), between which there is no significant difference (p = 0.61). Figure 6b shows that the average overall IFI of floodplain units that intersect urban areas is lower (median = 0.53, mean = 0.55) than that of floodplain units that do not (median = 0.79, mean = 0.77), which are considered rural. The difference in average overall IFI between rural and urban floodplains is significant using the Student's t-test (p < 0.0001). Figure 6c shows overall IFI decreasing with stream order for streams above third order (except for eighth order, which only includes two floodplain units). The differences between average IFI as stream order increases are significant between third and fourth (p < 0.0001), fourth and fifth (p < 0.0001), and fifth and sixth (p = 0.0002) order streams using Tukey HSD. The relationship between overall IFI and the area of the floodplain unit was also investigated to check for an area bias, but no meaningful relationship existed (R^2 = 0.02) (see Appendix A).

I also analyzed the functional and overall IFI data to determine the importance of each function to the overall IFI for each floodplain unit. Figure 7 shows the ratio between the functional IFI and the overall IFI value for each of the floodplain units. Ratios greater than one indicate that the function IFI is increasing the overall IFI, while ratios less than one indicate that the function IFI is reducing the overall IFI for that floodplain unit. On average, flood reduction and groundwater storage functional IFI are slightly higher than overall IFI, while sediment regulation, organics/solutes regulation, and habitat provision functional IFI are lower than overall IFI. Differences between the average ratios for all functions are significant except for sediment regulation and organics/solutes regulation using Tukey HSD (p values in Appendix A). I also investigated the standard deviation of the five function IFI values and the frequency and spatial distribution of the function with the minimum IFI value of the five functions (see Appendix A).

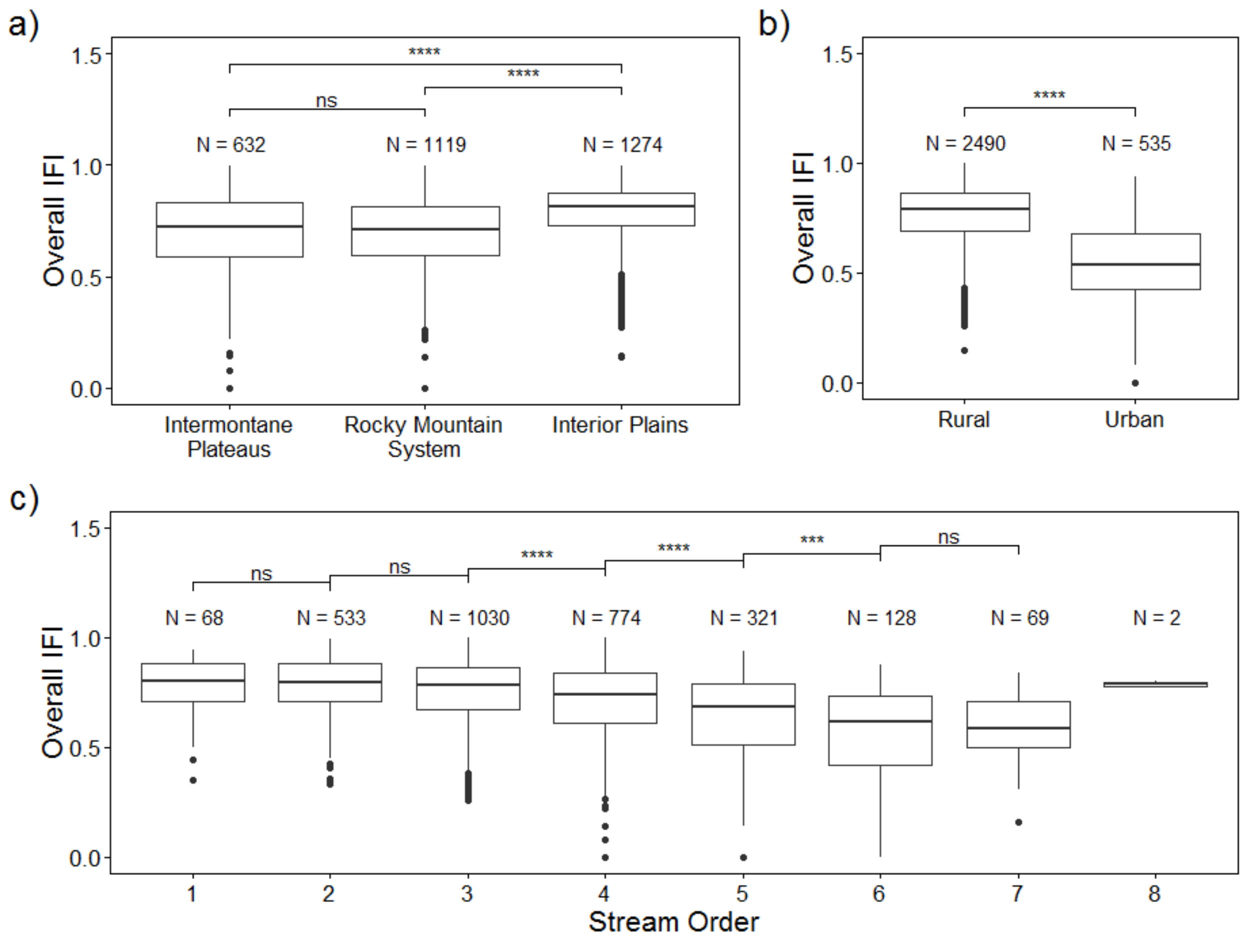

Figure 6. Analysis of IFI by a) physiographic region, b) rural vs urban, and c) stream order. Physiographic regions and urban areas are shown shaded in Figure 3. Statistical significance between means is indicated by ns (not significant), *, **, ****, or ****, indicating the *p* value is >0.05, <0.05, <0.01, <0.001, or <0.0001, respectively.

In comparing the computed overall IFI to ICI and density of wetlands, no meaningful relationships were found, as shown in Figure 8. Coefficients of determination were 0.05 for IFI versus ICI and 0.01 for IFI versus wetland density. However, despite the absence of a predictive relationship, the correlations of overall IFI to ICI and wetland density were both statistically significant (p < 0.0001). The regression of IFI and wetland density was also performed with floodplains separated by stream order, with no meaningful relationships found (see Appendix A).

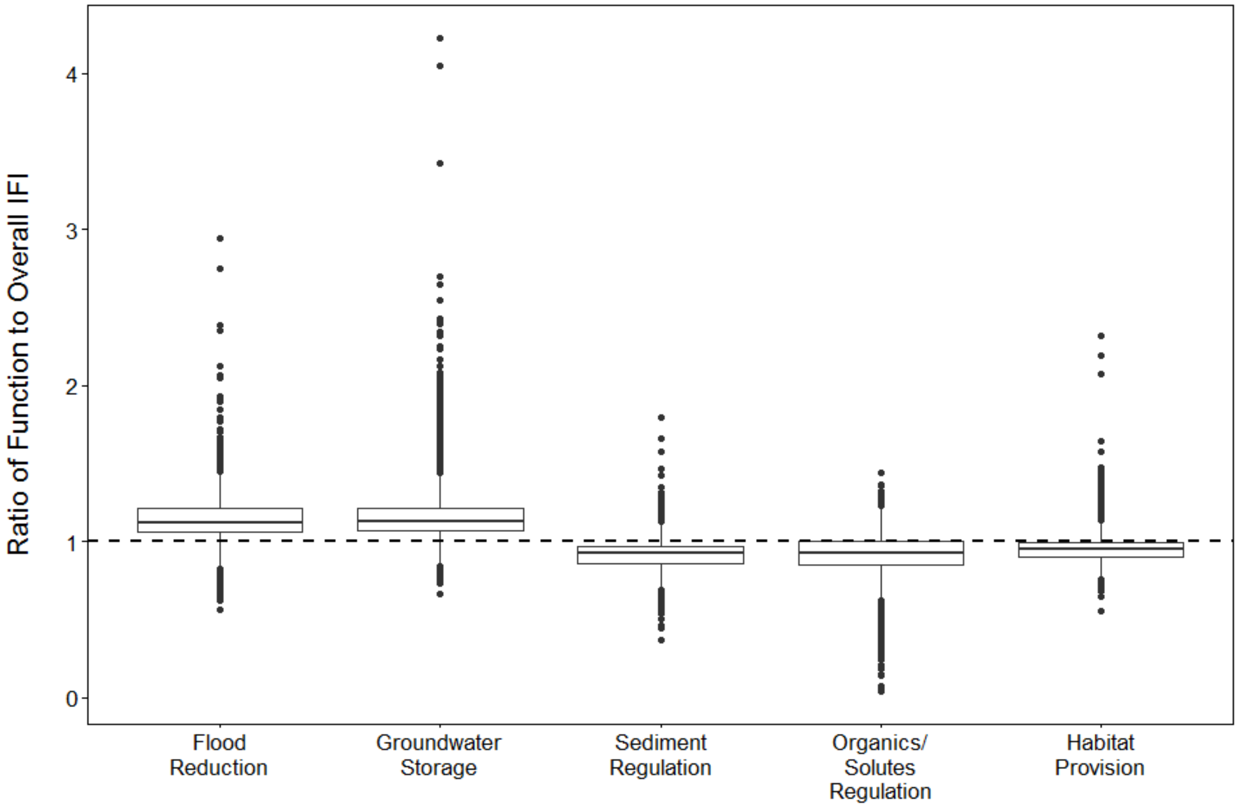

Figure 7. Ratio of functional IFI to overall IFI for the five floodplain functions. Ratios greater than one indicate that the function is increasing the overall IFI, while ratios less than one mean that the function is reducing the overall IFI.

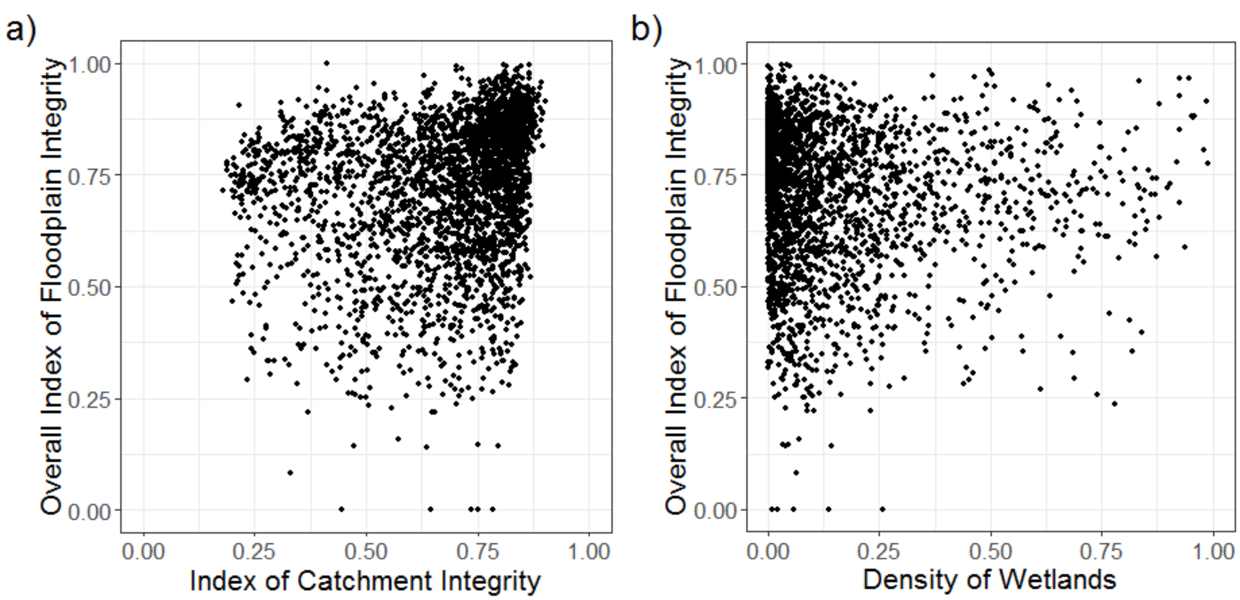

Figure 8. Comparison of overall IFI to a) ICI and b) wetland density. The relationships are not predictive ($R^2 < 0.1$), although they are statistically significant ($p < 0.0001$).

5 Discussion

The methodology developed to compute IFI was successfully applied to the state of Colorado. With functional and overall IFI mapped for Colorado's floodplains, it is possible to visualize the anthropogenic effect on floodplain integrity across the state. At present, this work is the first to quantify the integrity of specific floodplain functions instead of measuring floodplain health solely by ecological integrity. Because the IFI is numeric, it is possible to use the IFI values computed here for a broad range of analyses. The examples of IFI by physiographic region, stream order, and city versus rural represent analyses that can be performed, but any other spatial division or pattern could be investigated without recalculating IFI.

Similarly, because this methodology focuses on broadly available datasets, the computation of IFI can be repeated in a different area. The only Colorado-specific dataset used in this implementation of the IFI calculation was the groundwater well locations from the Colorado Decision Support System. All other datasets are available for the continental US. If alternate stressor datasets were identified for a new region, it would be straightforward to substitute these datasets into the IFI computational framework.

Regarding the results for Colorado, it is unsurprising that functional IFI values for the five floodplain functions are highly correlated (Appendix A). Many of the same stressors inhibit several functions (see Table 3), even though the specific manner in which the stressor affects the floodplain may vary between functions. The highly correlated functional IFI values are an inherent result of the interconnectedness of floodplain functions. A similar interdependence of stressors and indicators of functionality in floodplains has been noted in previous studies. For instance, Bouska et al. (2019) developed indicators of adaptive capacity for the Upper Mississippi River System and concluded that the indicators were often interdependent but that no single indicator appropriately described floodplain resilience. Furthermore, a review of the impact of altered flow regime on river and floodplain ecosystems by Bunn and Arthington (2002) noted the difficulty of distinguishing the impacts of flow alterations “from those of a myriad of other factors and interactions,” highlighting the complexity of stressor responses in floodplains.

5.1 IFI in Colorado

The functional and overall IFI values are left skewed (Figure 4), which is an inherent result of the distributions of the scaled stressor data used in their computation. As shown in Appendix A, the stressor density data are all skewed right, and thus the negative linear relationship between stressor density and IFI results in left skew of the IFI values. The two stressors that were not present in greater than 90 percent of the floodplain units were leveed area and groundwater wells, which were included in the calculation of the flood reduction and groundwater storage IFI, respectively. As a result, flood reduction and groundwater storage IFI show the highest skew and also have the most tendency to raise the overall IFI of the five functions (Figure 7). However, despite the relatively higher average IFI of flood reduction and groundwater storage, all five functions report a ratio of functional IFI to overall IFI above and below one for some floodplain units, showing that there was variability in the relative integrity of the functions despite their high correlation. This inter-function variability is quantified by the histogram of the standard deviation of the functional IFI values shown in Appendix A.

When mapped to the floodplains units, the computed IFI shows gradients in integrity (Figure 5). One conclusion to draw from these visible gradients is that the scale at which the floodplains were divided is appropriate. If a random distribution of IFI values were observed, it could imply that the division of the floodplains was too fine relative to the stressor data scale and average trends in stressor level were not captured. However, if the IFI changed minimally between floodplain units, it could signal that spatial trends in stressor density were masked by averaging over too large of an area. As neither a random nor uniform distribution of IFI values was produced, the HUC-12 division of the floodplains appears to be an acceptable scale for this methodology.

The analyses of IFI by physiographic region, urban versus rural, and stream order present an overview of spatial variations in floodplain integrity in Colorado. The analysis by stream order provides information about the effect on integrity of a floodplain's position within a watershed. Higher integrity is generally observed in the headwaters than in larger order streams, which makes sense considering that human activity tends to be focused around larger rivers and that headwater streams are often in less populated (and therefore less modified) areas. Also, floodplains that intersect urban areas have a significantly lower average integrity than those that do not, which also is supported by the fact that humans disturb floodplain function (Wohl, 2019), and humans are preferentially concentrated in urban areas. When considering the regional trends in floodplain integrity, I was surprised to see higher integrity in the plains than the other physiographic regions, especially considering that the largest cities in Colorado are also in the plains region. One possible explanation for this is relative recentness of development in the mountainous regions relative to the plains, which feeds into a time bias described further in Section 5.3. Additionally, different regions have different primary stressors. For the interior plains, the primary stressors are likely surface flow regulation and lowered groundwater table, which are both stressors that do not have a directly measured dataset. Accordingly, the regional differences in overall IFI may reflect more on regional changes in primary stressors and representativeness of the associated dataset than actual differences in integrity.

5.2 IFI validation

As IFI is intended as a comparative metric and has no physical meaning, it is difficult to validate the IFI results. I attempted to find datasets to use for comparison to the Colorado IFI results, but was unable to identify an appropriate measure of floodplain functionality. Most riverine integrity studies focus on watershed level or in-stream metrics with a strong emphasis on ecological integrity, which complicates the comparison with a multi-function floodplain specific metric like the IFI. However, IFI results for Colorado were compared to ICI from Thornbrugh et al. (2018) and wetland density to see if similar spatial patterns existed.

I was surprised to see very little correlation between IFI and ICI or wetland density. One implication of this is that catchment health is not an appropriate indicator of floodplain health, as their differing processes and forms make them distinct ecological units that must be evaluated individually. One notable difference between the ICI and IFI computation is that many catchment stressors are water quality related, which was not included as a floodplain stressor. For instance, one of the six watershed functions Thornbrugh et al. (2018) identified was regulation of water chemistry, which included mines, superfund sites, fertilizer application, industrial facilities, and wastewater treatment plants as stressors. The importance of water quality to the watershed integrity evaluation is reflected in the fact that IWI explained more than 25 percent of the variability in a water quality metric derived from the EPA's National Rivers and Streams Assessment (Thornbrugh et al., 2018; USEPA, 2016).

When considering the relationship between overall IFI and wetland density, there is no predictive relationship. However, Figure 8b appears to show a rough threshold where high densities of wetlands do not occur in floodplains with low overall IFI. Despite the lack of predictive relationships between ICI and wetland density, I have some confidence in the IFI results as the spatial analyses discussed in Section 5.1 match what is intuitively expected.

One final note on the comparison of overall IFI to ICI and wetland density is that the relationships were statistically significant, which means that there is evidence to support that the data are not entirely random. The high sample sizes of floodplain units likely contribute to this statistical significance. However, the low coefficients of determination for both comparisons demonstrate that, though significant, the relationships have negligible predictive power.

5.3 Limitations of the IFI method

Although the IFI approach presented in this paper is novel in its assessment of specific floodplain functions, there are also limitations that reduce the usefulness of this methodology. Likely the most impactful of these limitations is that the datasets available to quantify the stressors of floodplain functions vary in their representativeness. For instance, density of groundwater wells does not necessarily correspond directly to groundwater depletion, especially considering that no withdrawal volume is included in the dataset. This introduces uncertainty into the integrity estimate for groundwater storage.

One other stressor that is poorly represented by available data is the presence of large wood and forest stands. The Hansen et al. (2013) global forest loss dataset only contains forest loss occurring after 2000 and therefore does not represent the bulk of the deforestation in the state. This limited date range also serves to introduce a bias into the integrity assessment as forest loss is preferentially shown in regions of new development as opposed to areas where forest may have been cleared for development historically. A final note on the forest loss dataset is that it is also used to represent loss of large wood in the floodplain system as no other datasets quantify this at a broad enough scale. However, prevalence of large wood has been reduced through active log jam removal in Colorado (Wohl, 2019), not only deforestation, and therefore the forest loss dataset provides an incomplete quantification of this stressor. This limitation of poor stressor representativeness could be addressed with identification or creation of additional datasets that measure these human landscape alterations for large spatial extents.

Another notable limitation of this methodology is the assumption that the responses of functions to stressors are all equal and negatively linear (Thornbrugh et al., 2018). It is probable that certain stressors are more influential to given functions. Additionally, certain relationships between stressors and functionality may be non-linear and have thresholds where functionality changes drastically. Although there are few studies that specifically explore the responses of floodplain functions to stressors, there is ample evidence that thresholds exist in floodplain morphology (Livers et al., 2018; Meyer, 2001; Wohl, 2019), so it is probable that they exist in floodplain functionality as well. As new research elucidates more complex functional responses, substituting these relationships into the IFI computation is a minor process modification that can improve the credibility of the IFI metric. Specifically, studies that measure floodplain functionality at a variety of stressor levels would provide useful insight. For instance, an investigation could be performed to identify if a threshold density of impervious surface exists below which groundwater recharge is no longer impaired.

One additional limitation of the IFI methodology is that the computed IFI is scaled relative to the datasets included, which complicates comparisons between different implementations of the methodology. Because the stressor data are rescaled relative to the 90th percentile of the data included in the analysis, the IFI calculated for Colorado in this investigation are not directly comparable to results calculated for other locations. Although insight could still be gained in comparing the distributions or spatial patterns of IFI calculated with two different datasets, the best practice would be to rescale the stressor data using datasets that cover the entire area of interest before calculating IFI.

A final consideration for the results of the IFI calculation is that the floodplain delineation I used in this study is a hydraulically modeled 100-year floodplain. If the floodplain was delineated for a different return interval, or delineated hydrogeomorphically, the results would change as they are dependent on the precise floodplain delineation. However, I would expect changes in the results with floodplain delineation to be small as stressors tend to have gradual spatial changes, so slight floodplain boundary shifts will not drastically change the stressor levels observed in the floodplain.

5.4 Future work

As mentioned in the discussion of limitations of the IFI method, there are opportunities to expand upon the methodology and implementation presented in this paper. First, incorporation of new or more representative stressor datasets will contribute to the trustworthiness of the IFI assessment. Secondly, the relationships between floodplain functions and their stressors should be updated as new research provides additional information into the complexities of floodplain response. Finally, this methodology can be applied to additional and potentially larger areas, such as the continental United States, to both serve as a test of the methodology's robustness and to provide useful information about the integrity of floodplain functions across a larger region.

6 Conclusion

This study presents a novel methodology to assess the integrity of floodplains and their functions over broad spatial scales and then demonstrates the methodology in the state of Colorado. The IFI methodology is based upon identifying and quantifying anthropogenic stressors that inhibit critical floodplain functions. The prevalence of these stressors is used to evaluate the relative integrity of five floodplain functions: flood reduction, groundwater storage, sediment retention, organics and solutes retention, and habitat provision, as well as evaluating overall integrity. For Colorado, overall floodplain integrity decreased with stream order above third order streams. Overall integrity was also lower for floodplain that intersected urban areas. Finally, regional difference in IFI were identified, with the Interior Plains having higher integrity than the Intermontane Plateaus or Rocky Mountain System. The IFI methodology as presented in this study provides an important first step towards quantifying changes to floodplain integrity and the results of this study can provide a useful management tool for agencies that perform floodplain restoration projects. By highlighting the functions and the areas with the highest reductions in functionality, the IFI can enable more efficient restoration efforts by targeting the areas of greatest need early in the restoration planning process. The trustworthiness of the IFI is currently limited by the datasets available and the state of knowledge of floodplain functional response. Progress in either of these areas could easily be incorporated into the IFI methodology to create a more informative metric. Despite this potential for improvement, I believe the IFI methodology can be applied to additional areas to provide key high-level guidance to floodplain restoration projects. Understanding the extent of human influence on floodplain functionality is a crucial step towards preserving floodplains and their associated benefits.

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Appendix A: Additional investigations

CONTENTS OF APPENDIX A

1. Hydrologic alteration aggradation method exploration

Because the hydrologic alteration data were available for streamlines and the delineated floodplain was not explicitly linked to streamlines, it was necessary to aggregate the hydrologic alteration values from the streamline scale to floodplain unit scale. Five different methods were tested for aggregating the individual flow line hydrologic alteration values to the larger floodplain units (which are divided by HUC-12). They are explained, with rationale, below:

1) Maximum value: The maximum probability of hydrologic alteration present within each HUC-12 is assigned to the entire floodplain within that HUC-12. This is the most conservative, and also relies on the assumption that the majority of the mapped floodplain and the high alteration values are both generally associated with the main stem in each HUC-12.
2) Mean value: The arithmetic mean of all probability of hydrologic alteration values present within the HUC-12 is applied to the entire floodplain within the HUC-12. Assumes that floodplain alteration represents a combination of hydrologic alteration within the basin.
3) Length-weighted mean: The hydrologic alteration probability of each stream segment is multiplied by the stream segment length. The length-metric product is summed for each HUC-12 and divided by the total stream length for each HUC-12 to provide a length-weighted estimate of the probability of hydrologic alteration. This estimate is applied to the floodplain within the HUC-12. This method assumes that the length of the stream within the HUC-12 determines its importance to the floodplain alteration.
4) Order-weighted mean: The stream order (NHD+ V1 values) of each segment is multiplied by the hydrologic alteration probability of each stream segment. The order-metric product is summed for each HUC-12 and divided by the sum of the stream orders for each HUC-12 to provide a stream order-weighted estimate of the probability of hydrologic alteration. This estimate is applied to the floodplain within the HUC-12. This method assumes that

the mapped floodplain is preferentially associated with the larger order streams and therefore they receive higher weight.

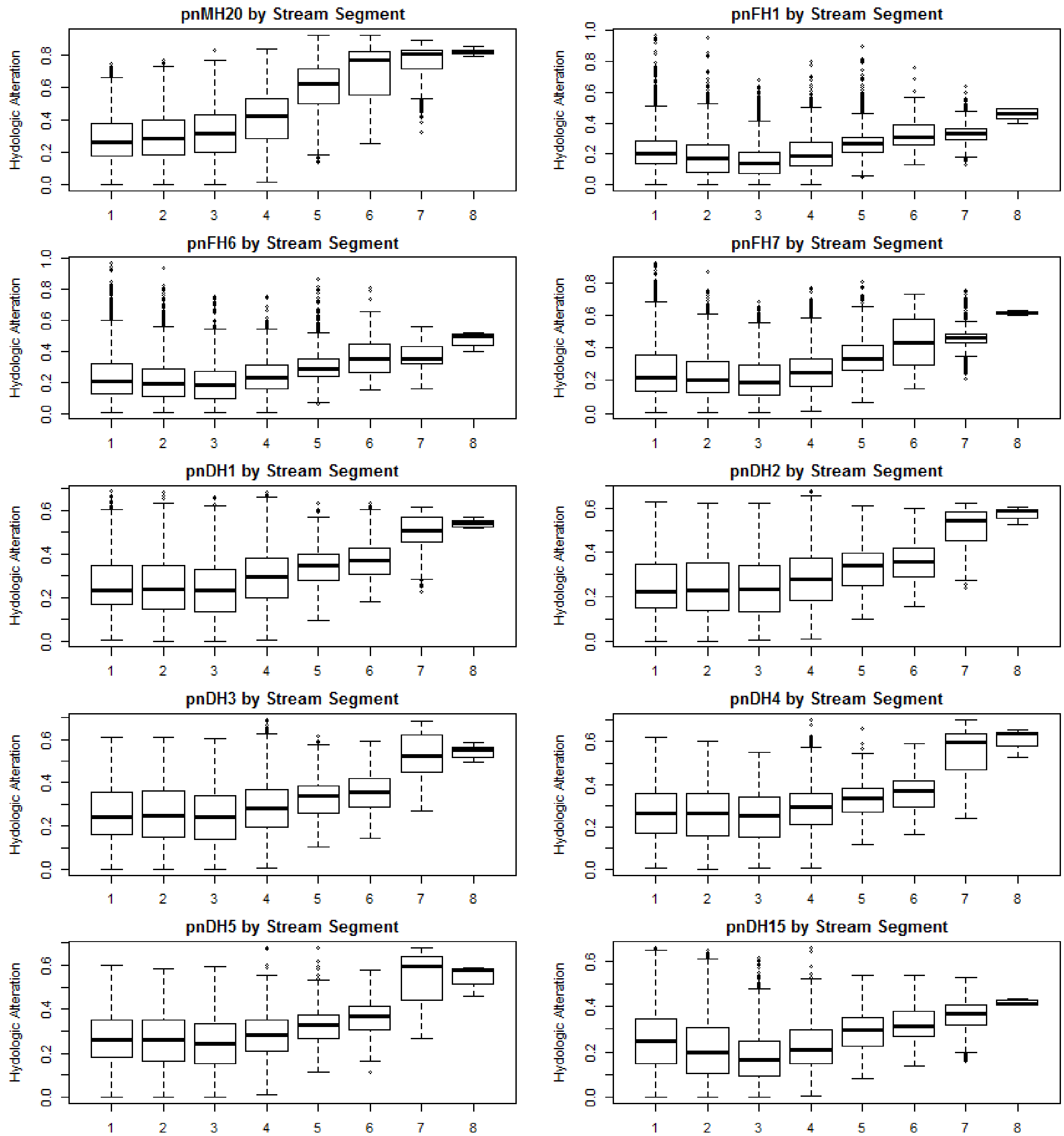
5) Maximum order only mean: The maximum stream order of all stream segments present in the HUC-12 is determined. The stream segments in the HUC-12 that are of the maximum order are selected, and then the hydrologic alteration probability values for these maximum order segments are averaged within each HUC-12. This "max order mean" is applied to the floodplain within that HUC-12. This method assumes that the floodplain is associated with the highest order streams within the catchment and therefore the alteration of these streams reflects floodplain alteration.

To determine which method was most appropriate to aggregate stream-level data to the floodplain unit, the data were visually compared with boxplots. From the boxplots, the center and spread of all 10 hydraulic alteration metrics was similar for methods 2-4. For all metrics, the highest average value and largest spread was seen with method 1 (statistically difference from all other methods for all metrics using Tukey significant difference). Method 5 produced a slightly higher center and a higher top end of the spread than methods 2-4 for most metrics. This difference was statistically significant from methods 2-4 for some, but not all, hydrologic alteration metrics.

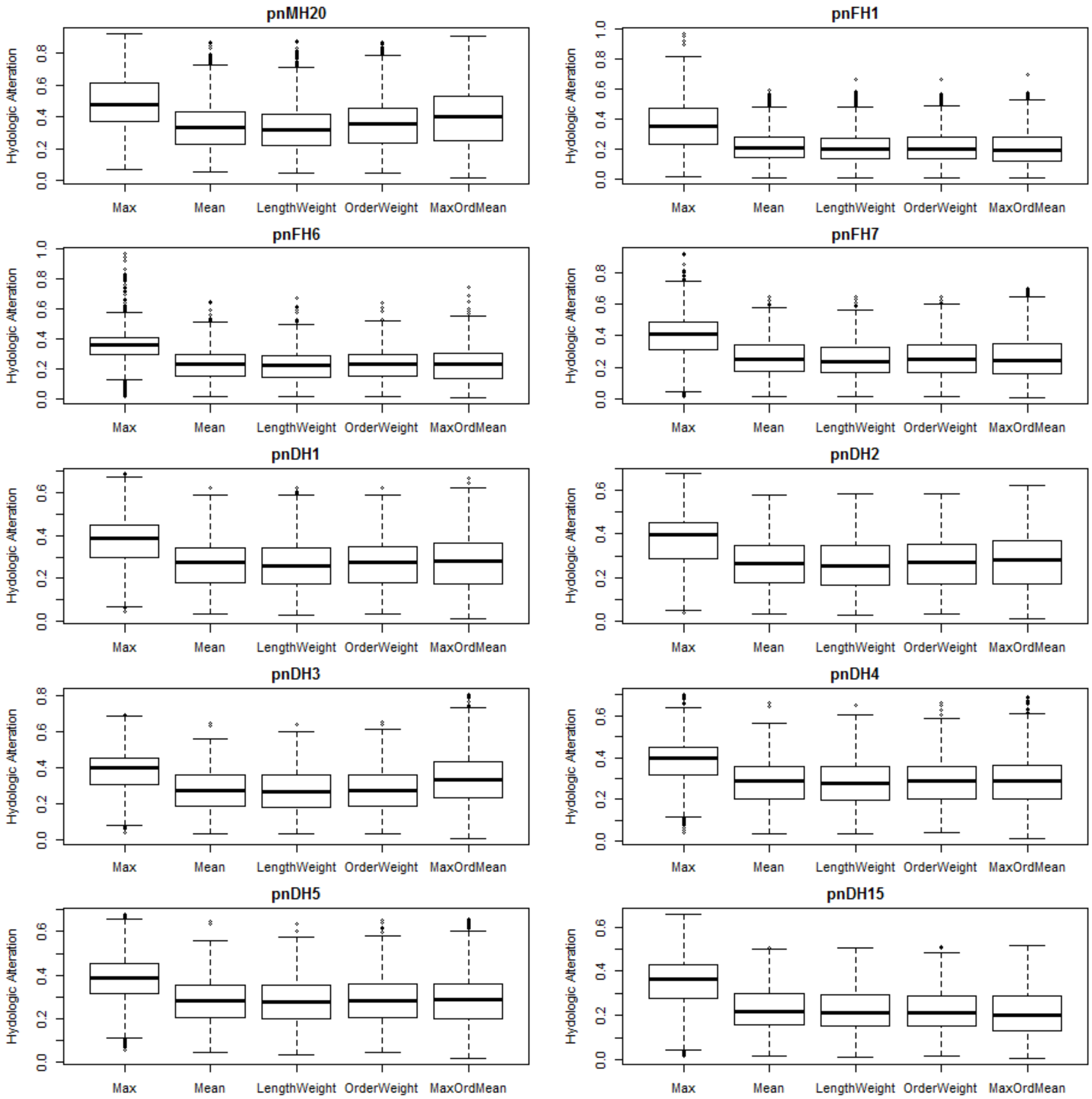
In addition, to test the assumption the hydrologic alteration increases with increasing stream order, the hydrologic alteration for all 64,742 stream segments in Colorado was plotted by stream order in box plots. Visual inspection shows a generally increasing alteration with stream order, especially for stream orders 4 and above. Several metrics show a slight decline from order 1 to order 3 streams, but it is not as pronounced as the increase at higher orders.

Finally, plots were made to check if the trends observed in the stream segment data were also present in the floodplain unit aggregated data. Hydrologic alteration data for all floodplain units were plotted according to the maximum stream order present within the HUC-12 of the floodplain unit. The data for aggregation methods 1, 2 and 5 were plotted. There was minimal difference in trends between the methods. It appeared that Method 2 produced les of an increase in hydrologic alteration with stream order than methods 1 or 5. In comparison the stream segment plots, methods 2 and 5 of the floodplain unit plots showed slightly more of a decrease between stream orders 1 to 3 for almost all metrics.

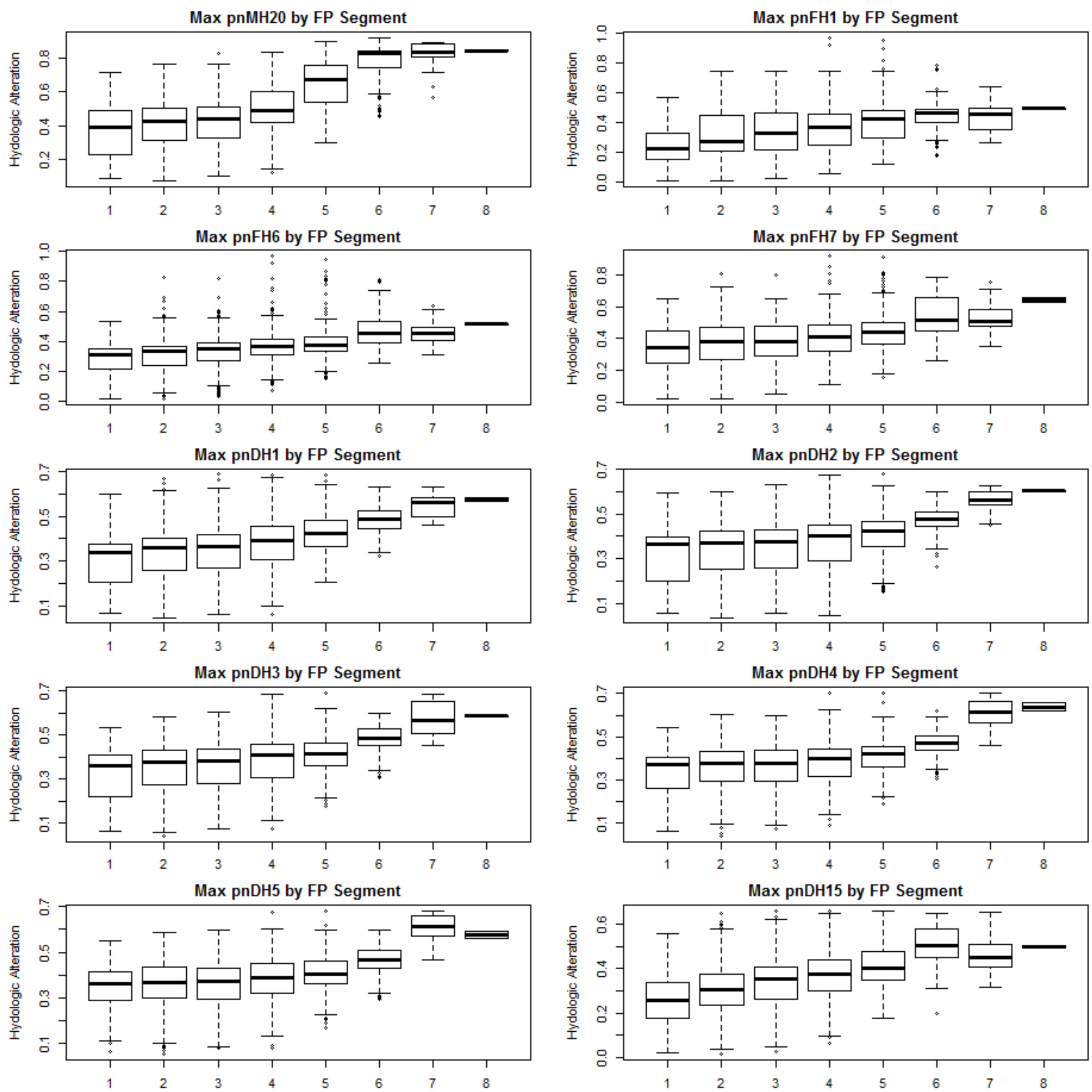
In considering all the methods discussed above and their differences or lack thereof, method 5 of averaging the hydrologic alteration probabilities for the highest order stream segments in each HUC-12 was selected. It did not produce significantly different results from methods 2-4, reproduced the patterns seen in the stream segment analysis, and had the most realistic physical explanation when considering with which stream segments the floodplain areas would be associated.



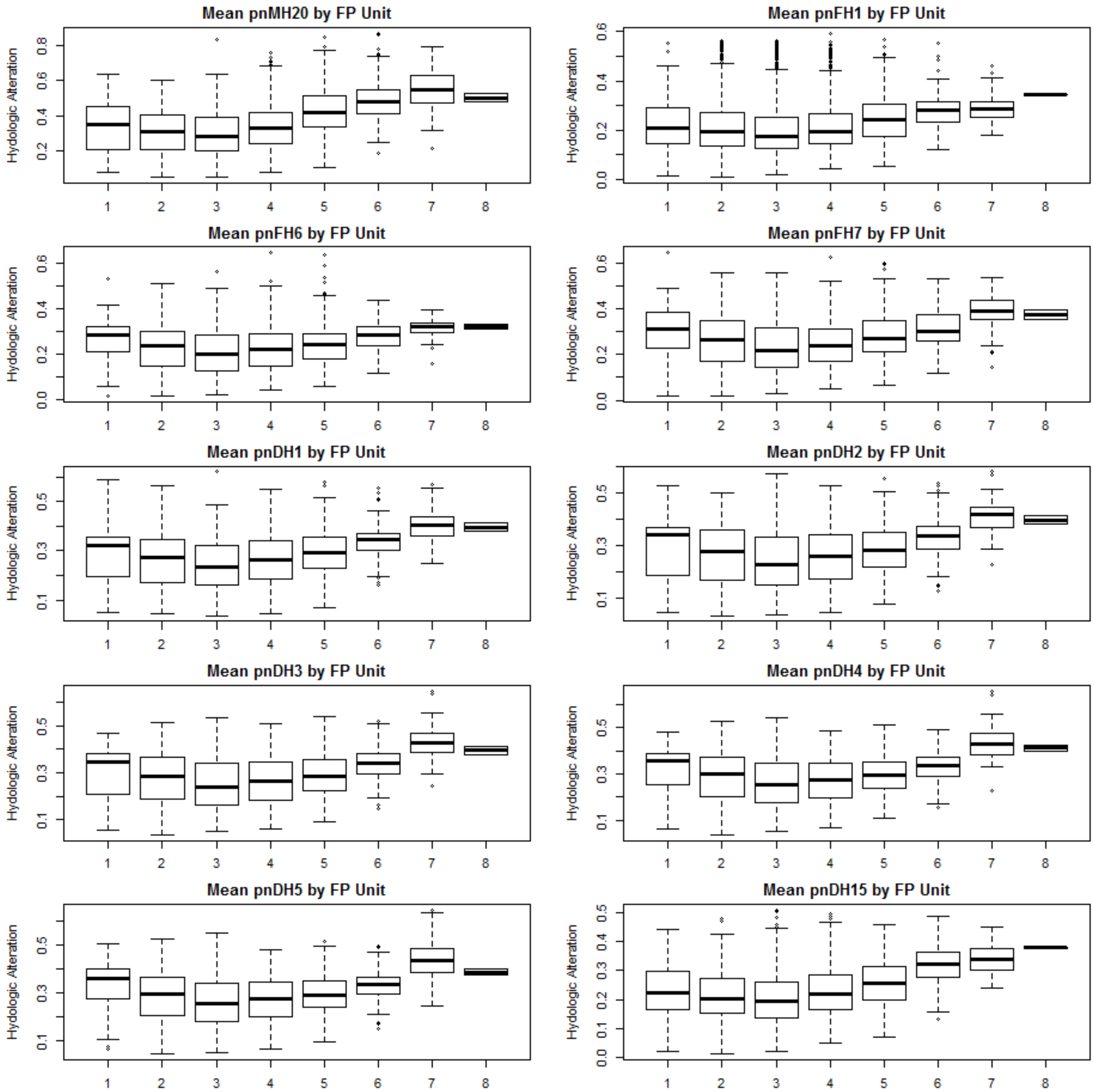
These boxplots show the probability of hydrologic alteration values by stream order for the NHDPlus V1 segments for which they were calculated. This is presented for the 10 relevant indicators of hydrologic alteration.



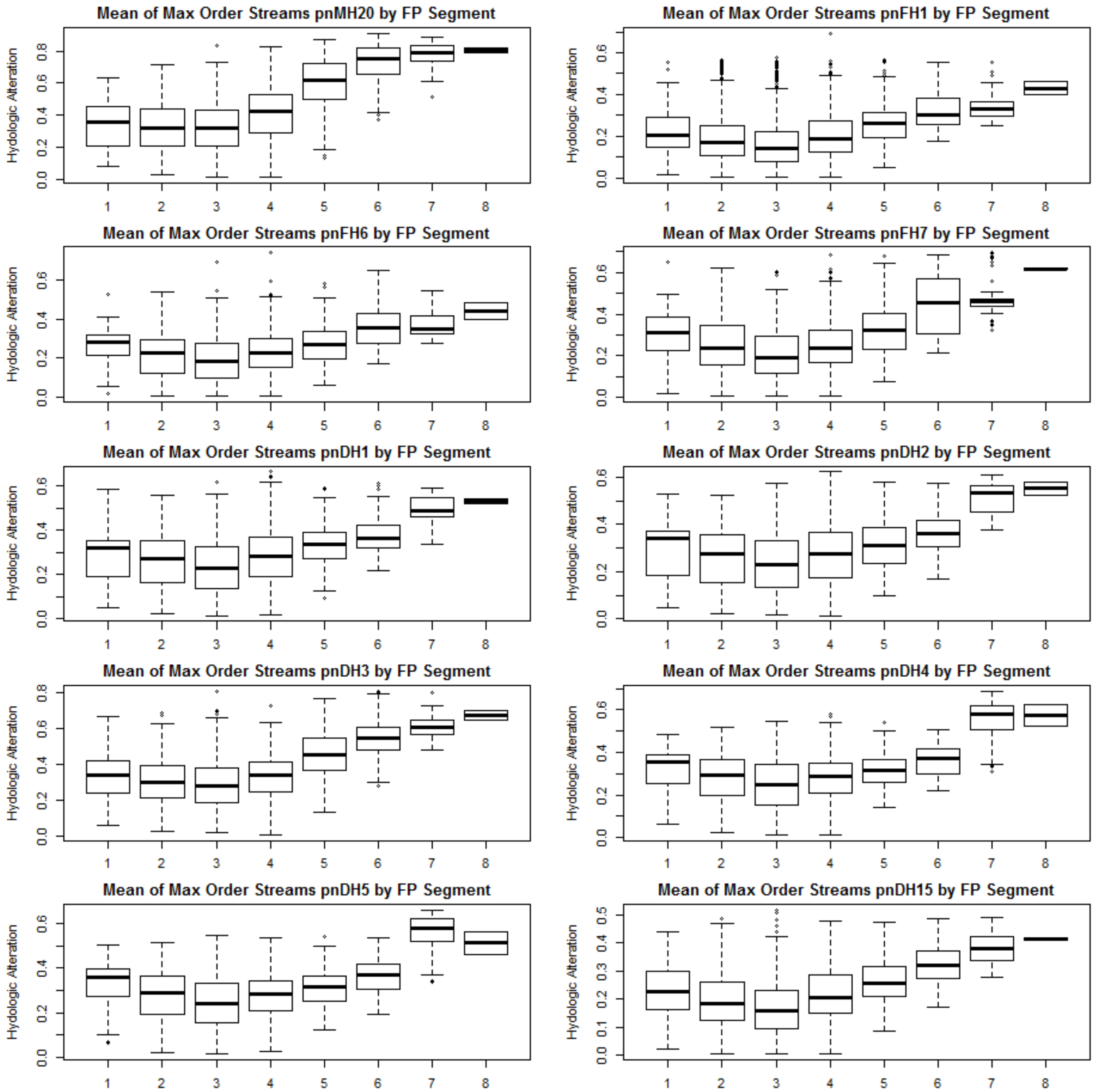
This figure compares methods 1-5 described above for aggregating the stream level probabilities of hydrologic alteration to the floodplain unit scale. This is presented for the 10 relevant indicators of hydrologic alteration.



This figure shows the results of using method 1, or maximum values per HUC-12, to aggregate to the floodplain unit level by stream order. This is presented for the 10 relevant indicators of hydrologic alteration.



This figure shows the results of using method 2, or mean of values per HUC-12, to aggregate to the floodplain unit level by stream order. This is presented for the 10 relevant indicators of hydrologic alteration.



This figure shows the results of using method 5, or mean of maximum stream order values per HUC-12, to aggregate to the floodplain unit level by stream order. This is presented for the 10 relevant indicators of hydrologic alteration.

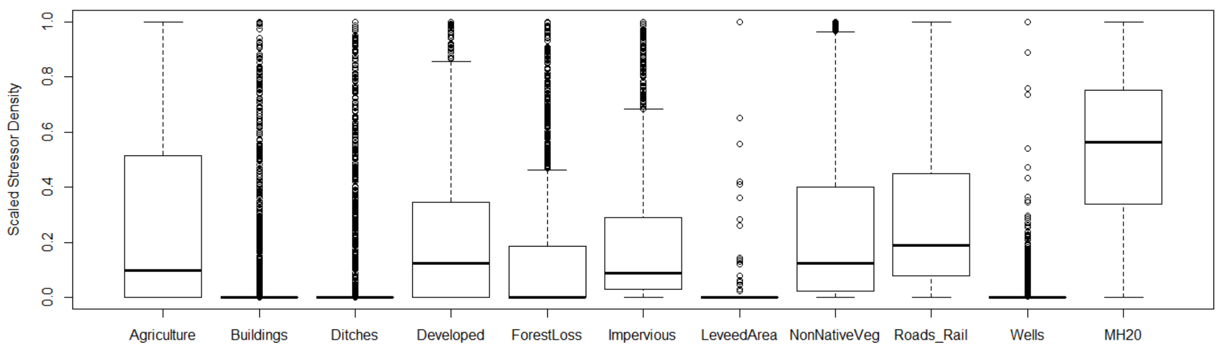
2. Scaled stressor data

The density of each stressor in each floodplain was calculated and then rescaled. It was decided to rescale the data relative to the 90th percentile of each data set, unless the 90th percentile was still 0, in which case the data was rescaled relative to the maximum value (for levees and wells). The 90th percentile was chosen as it limits the influence of exceptionally high outliers while providing significantly more definition with the lower 90% of the data. All values higher than the 90th percentile were given a stressor value of 1, or maximum density. Consideration for re-scaling included the following:

1) The original scale had no consistent scaling as the different types of data were scaled differently (i.e. lines and points vs. areas). Lines and point were already scaled relative to a local maximum value.
2) For some of the stressors, 100% coverage is not a reasonable value and therefore 100% coverage does not correspond to complete lack of function (eg buildings).
3) There is not sufficient research to determine the relative important of each stressor to each function, so the implication the 100% agriculture and 100% impervious surface should be counted equally has no theoretical base.
4) Covering 0% of the area of the floodplain should correspond to no impact, but covering 100% of the area does not necessarily indicate the highest possible impact as 100% is often not a feasible value.
5) The changes in stressor abundance at low values are likely proportionately more important to the processes occurring in the floodplain (e.g. a change from 0 to 10% impervious is more impactful to floodplain function than 80% to 90%).
6) The main goal of the IFI is to compare floodplains in Colorado to each other, and therefore scaling the stressor levels relative to the values present currently is more important than the scaling to a theoretical worst case scenario.

Some limitations of this rescaling procedure are as follows:

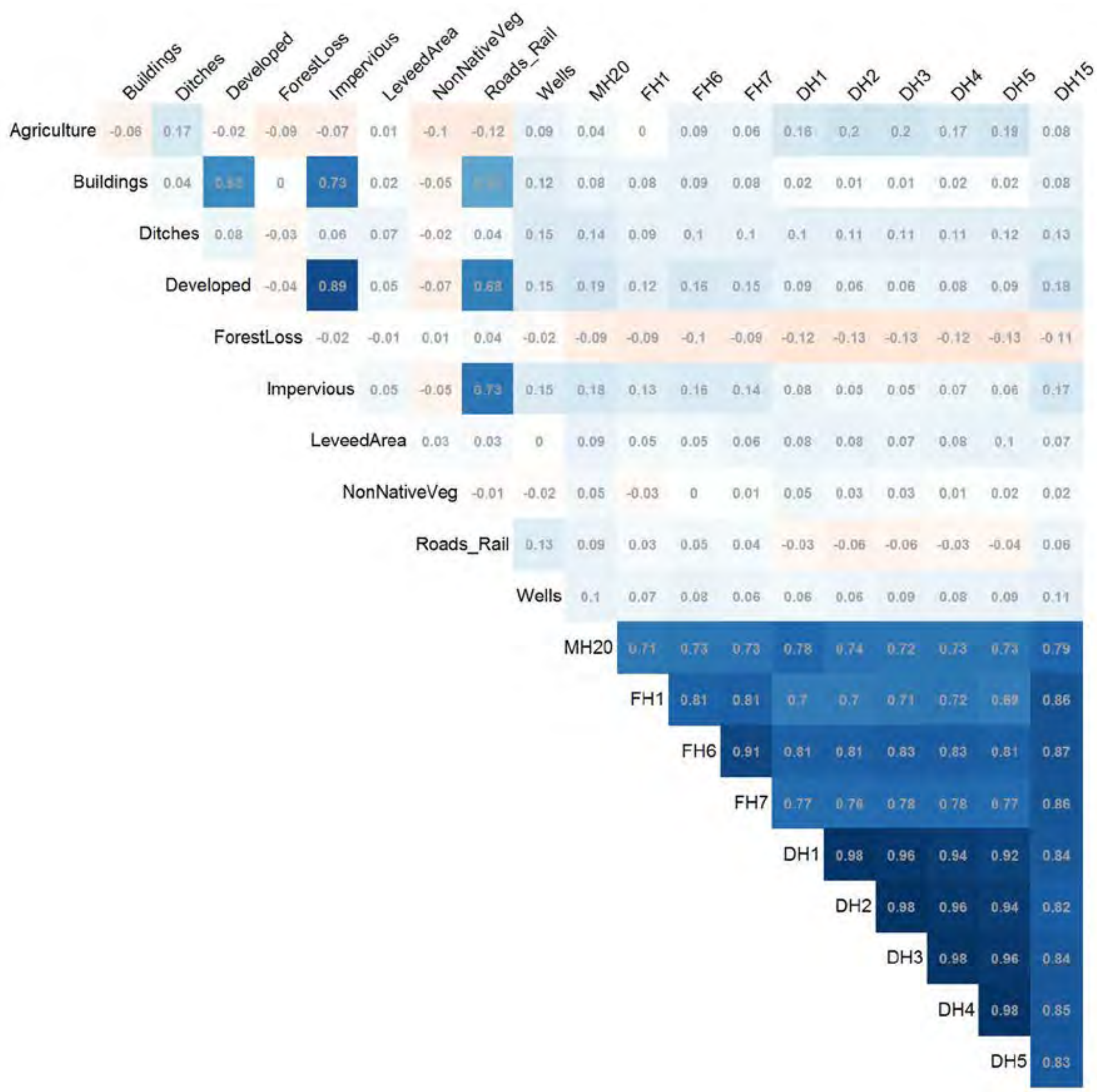
1) Still creates inconsistent scaling as 2 of the data sets are rescaled to the max instead of 90th percentile.
2) Sets 10% (303) data points to 1, which means information about the differences in these floodplains is lost.
3) Makes the methodology much more dependent on the input datasets – rescaling makes make it more difficult to compare results of separate computations of IFI.



This figure shows the distribution of the scaled stressor densities for each of the 11 stressor datasets.

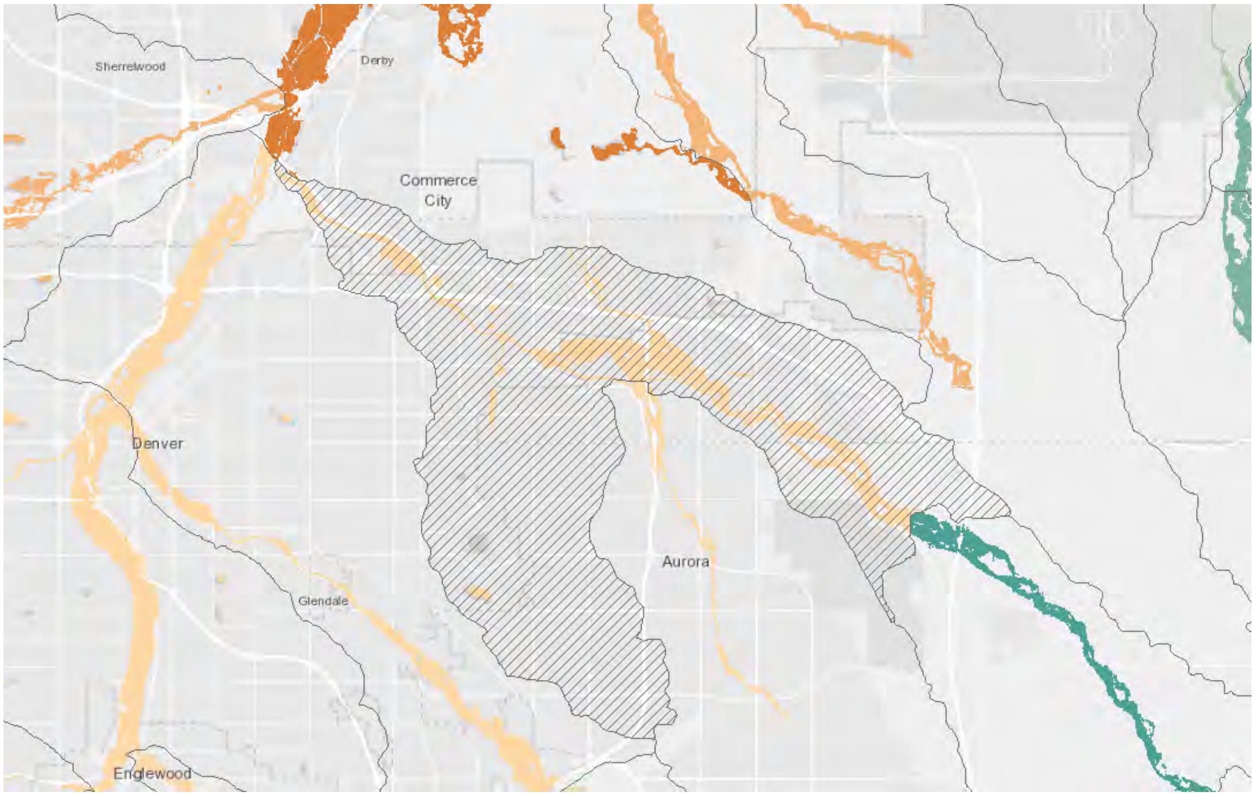
3. Correlation of stressor data

In order to avoid over-weighting a given stressor in calculation of the functional IFI, the stressor data were analyzed for correlation. For any two stressors which had a Pearson's correlation coefficient of 0.7 or greater, only one of the two stressors was used in the calculation of the functional IFI. The stressor that was included of the two correlated stressors was determined based on a judgement of relevance to the function informed by the literature review. Additionally, as the majority of the hydrologic alteration metrics had correlation coefficients greater than 0.7, only one metric was included in the IFI calculation. A correlation matrix of the stressor data is shown below.



4. Example of IFI calculation

The IFI calculation process is shown for the floodplain unit associated with HUC-12 101900030204 near Denver, shown below.



First, the scaled stressor densities for this floodplain unit are computed from all of the stressor datasets, with the results shown below.

Stressor	Scaled Value	Stressor	Scaled Value
Agriculture Area	0.148	Leveed Area	0.0
Buildings	1.0	Non-Native Vegetation	0.256
Ditches/Canals	0.801	Roads & Railroads	1.0
Developed Area	1.0	Groundwater Wells	0.080
Forest Loss	0.086	Hydrologic Alteration	0.894
Impervious Area	1.0		

From these stressors, each function IFI can be calculated.

Flood reduction: Buildings, Developed Area, Forest Loss, Leveed Area, Roads and Railroads

$$IFI_{floods} = 1 - \frac{1.0 + 1.0 + 0.086 + 1.0 + 0}{5} = 1 - 0.617 = 0.383$$

Groundwater storage: Agriculture Area, Ditches/Canals, Forest Loss, Impervious Area, Groundwater Wells

$$IFI_{groundwater} = 1 - \frac{0.148 + 0.801 + 0.086 + 1.0 + 0.080}{5} = 1 - 0.423 = 0.577$$

Sediment regulation: Agriculture Area, Forest Loss, Roads and Railroads, Hydrologic Alteration

$$IFI_{sediment} = 1 - \frac{0.148 + 0.086 + 1.0 + 0.894}{4} = 1 - 0.532 = 0.468$$

Organics/Solutes regulation: Forest Loss, Impervious Area, Hydrologic Alteration (Roads and Railroads not included because of high correlation)

$$IFI_{org/sol} = 1 - \frac{0.086 + 1.0 + 0.894}{3} = 1 - 0.660 = 0.340$$

Habitat provision: Agriculture Area, Developed Area, Forest Loss, Non-Native Vegetation, Roads and Railroads, Hydrologic Alteration

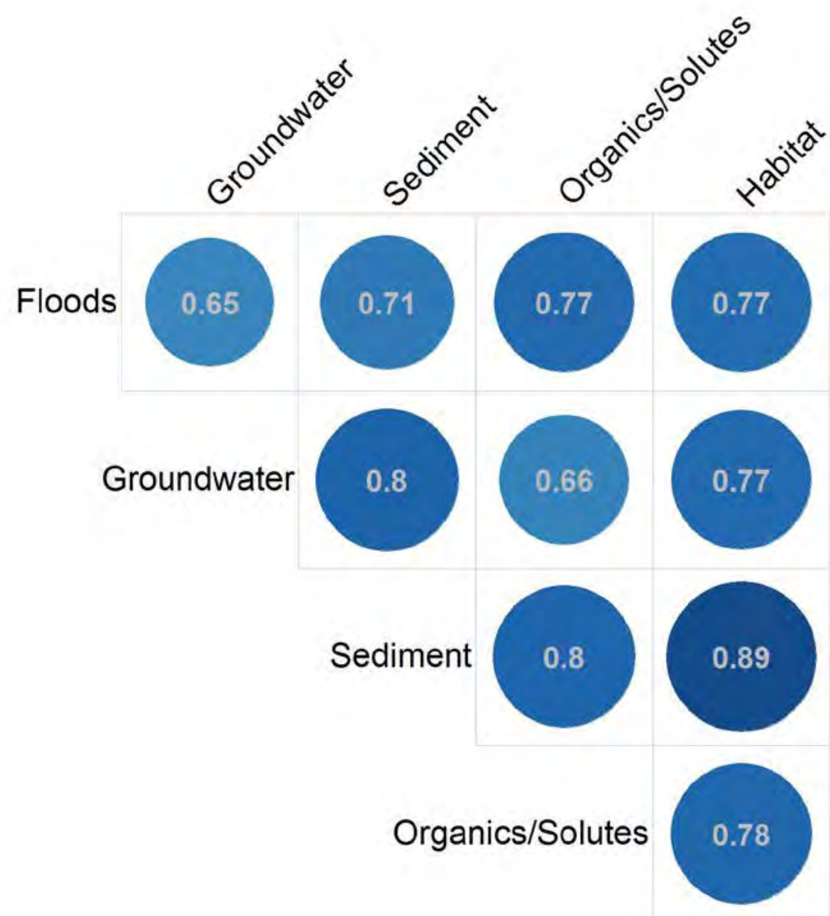
$$IFI_{habitat} = 1 - \frac{0.148 + 1.0 + 0.086 + 0.256 + 1.0 + 0.894}{6} = 1 - 0.564 = 0.436$$

The overall IFI is calculated as the geometric mean of the five functional IFI values.

$$IFI_{overall} = (0.383 * 0.577 * 0.468 * 0.340 * 0.436)^{\frac{1}{5}} = \mathbf{0.434}$$

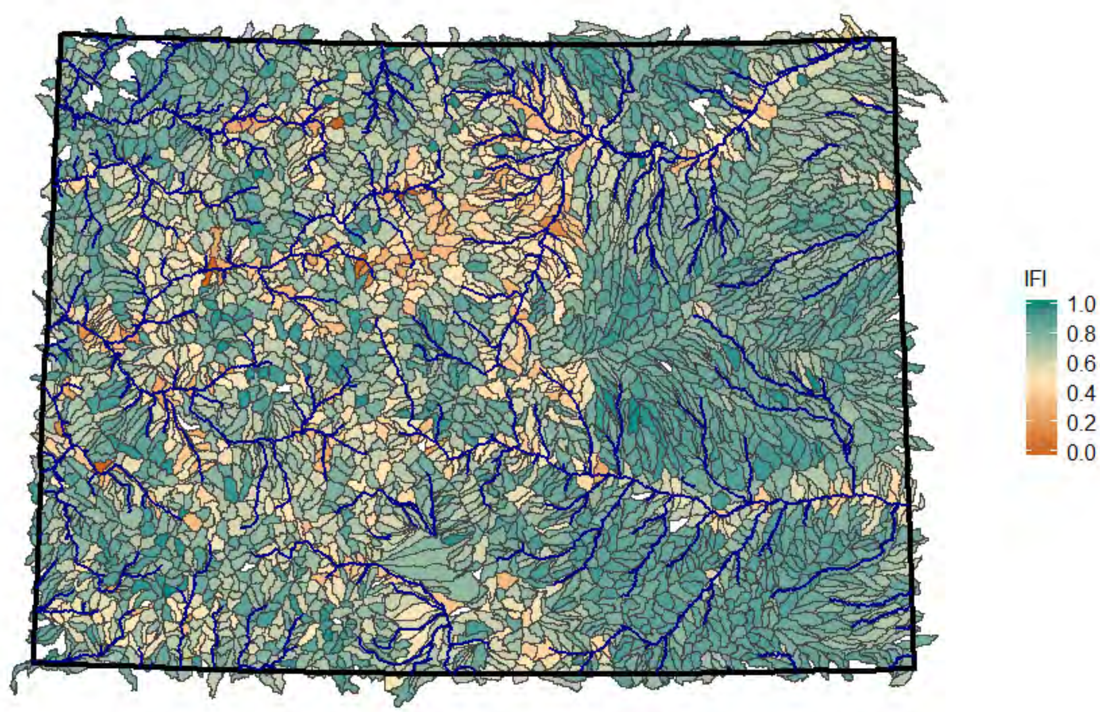
5. Correlation of functional IFI values

A correlation analysis was performed on the IFI values calculated for each of the five floodplain functions. Pearson's correlation coefficients are reported in the correlation matrix shown below. High correlation is generally seen, with the highest correlations occurring for functions which have the most overlapping stressor data (e.g. sediment regulation and habitat provision, which share four datasets).



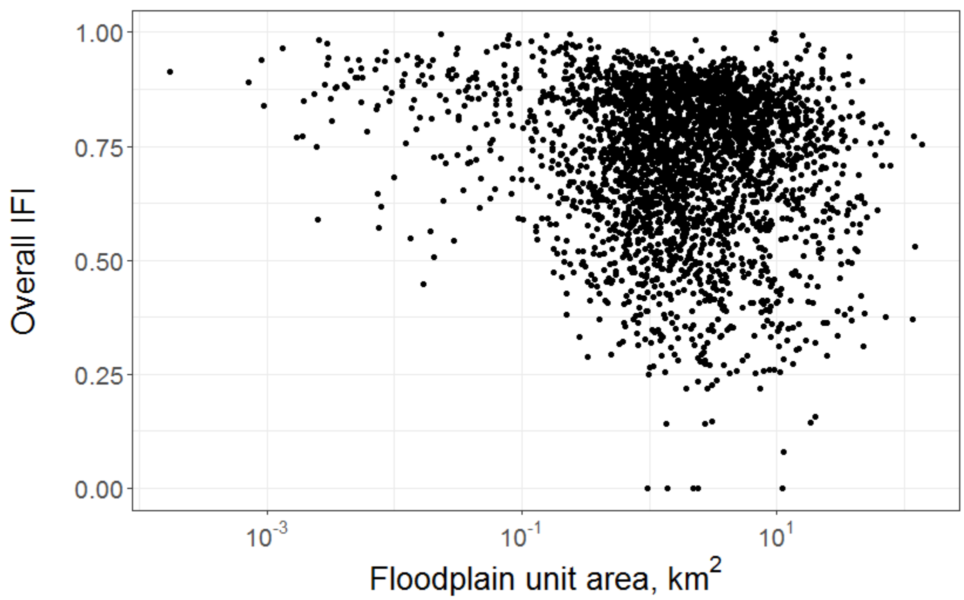
6. Overall IFI mapped to HUC-12

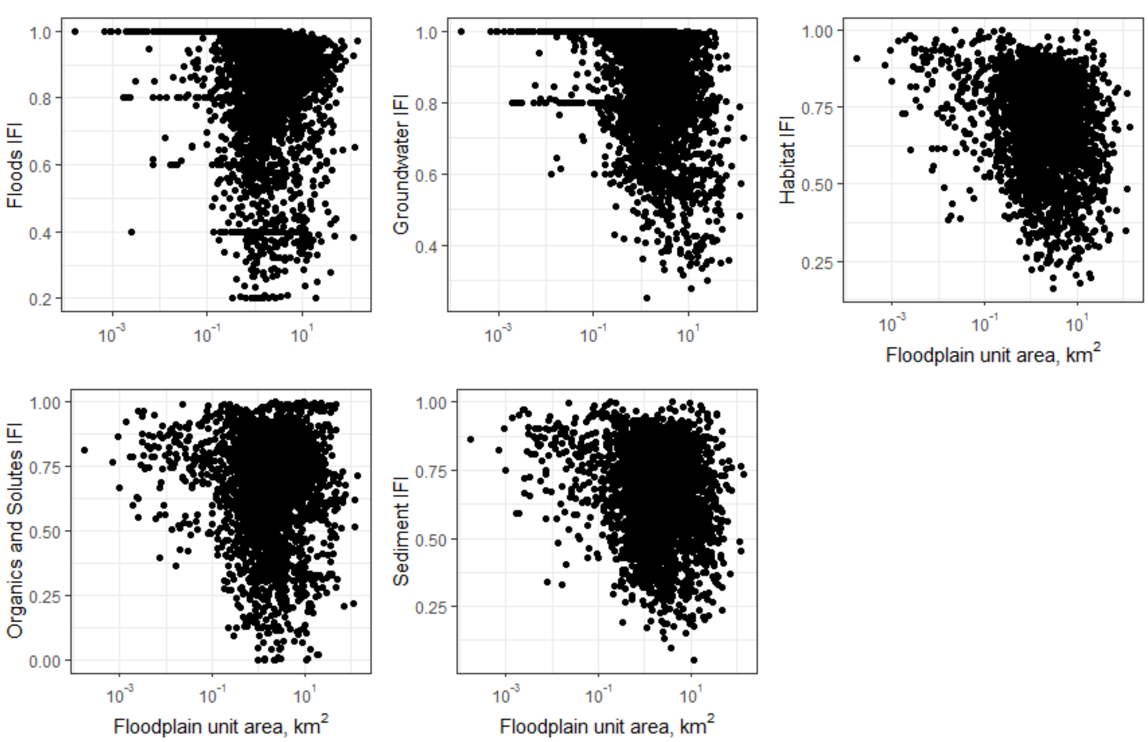
Because the area of floodplain in Colorado is small relative to the area of the state, it is difficult to visualize the patterns in floodplain integrity for the entire state simultaneously. To clarify the patterns in integrity, the HUC-12 units were colored according to the overall IFI of the floodplain unit contained within. Stream lines above fourth order are also included to show trends in IFI dependent on the location in the watershed.



7. Overall IFI vs floodplain unit area

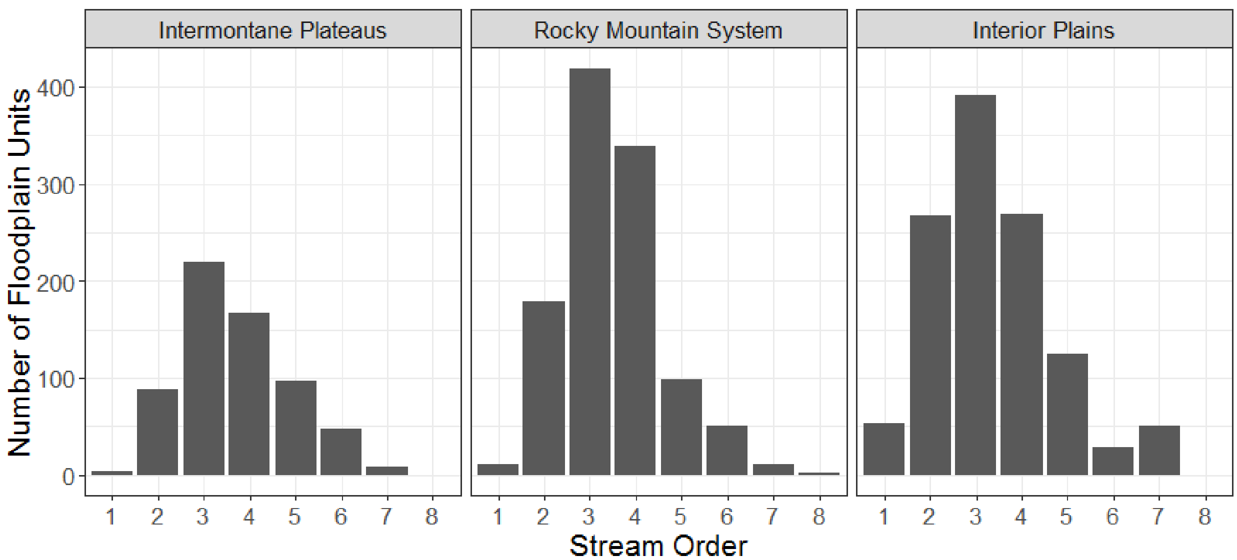
To check for floodplain area bias in the estimation of floodplain integrity, a regression was performed on the overall IFI value versus the area of the floodplain unit for which that value was computed. As shown below, no meaningful relationship was found, with an R^2 value of 0.02. The investigation was repeated for each functional IFI with no meaningful correlations found.





8. Stream order by physiographic region

When overall IFI was analyzed by physiographic region, it was noted that the Interior Plains had a significantly higher average integrity than the Rocky Mountain System. As this was unexpected, an investigation into the impact of stream order was conducted to ensure that stream order was not a lurking third variable, i.e. the Interior Plains showed higher integrity because there are more low order floodplain units in the plains and low order floodplain units were shown to have higher average floodplain integrity. However, as shown in the figure below, the distribution of stream order of the floodplain units is approximately the same between the three physiographic regions. The differences in stream order distribution were determined to be too minor to account for the difference in average overall IFI between the regions.

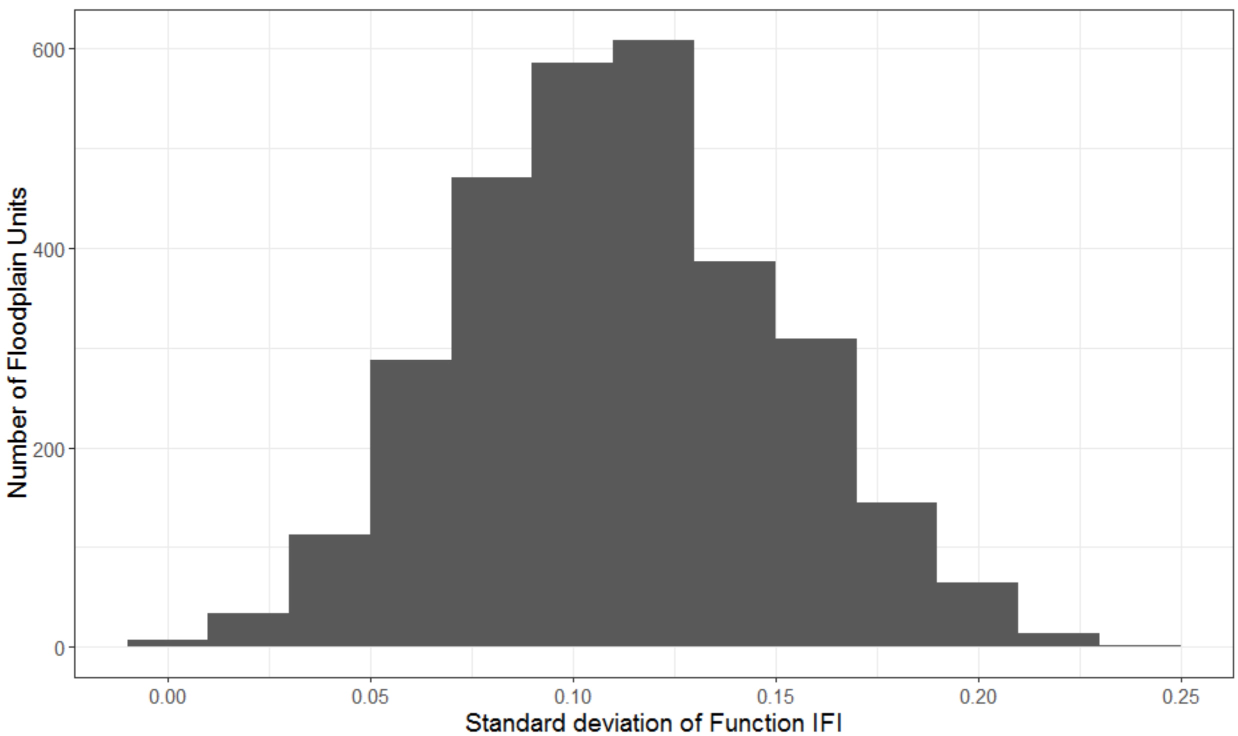


9. Functional IFI sensitivity and variability

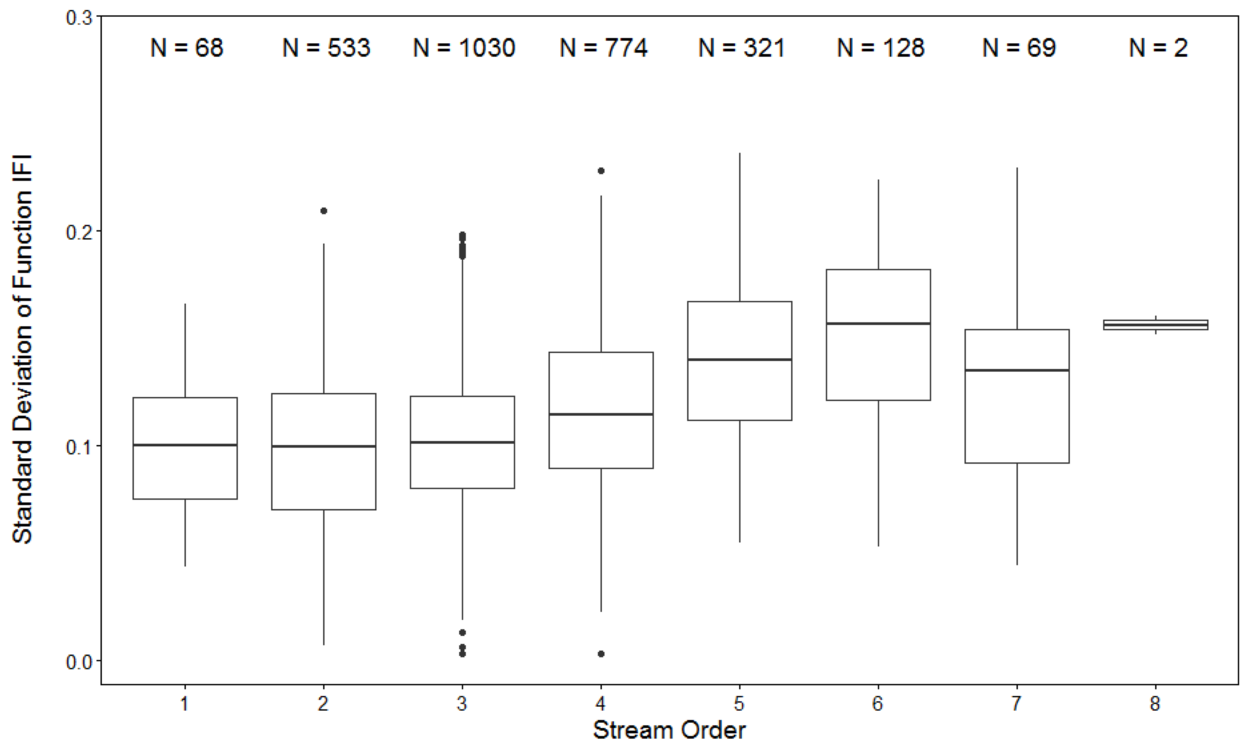
Investigations were performed to identify how the functional IFI varied for the same floodplain and how each functional value affected the overall IFI. In considering the ratios of the individual functional IFI to the overall IFI (Figure 7), the p-values for the difference in average ratio between functions are summarized in the matrix below.

p-value	Flood reduction	Groundwater storage	Sediment regulation	Organics/solutes regulation	Habitat provision
Flood reduction	-	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Groundwater storage	< 0.0001	-	< 0.0001	< 0.0001	< 0.0001
Sediment regulation	< 0.0001	< 0.0001	-	1.00	< 0.0001
Organics/solutes regulation	< 0.0001	< 0.0001	1.00	-	< 0.0001
Habitat provision	< 0.0001	< 0.0001	< 0.0001	< 0.0001	-

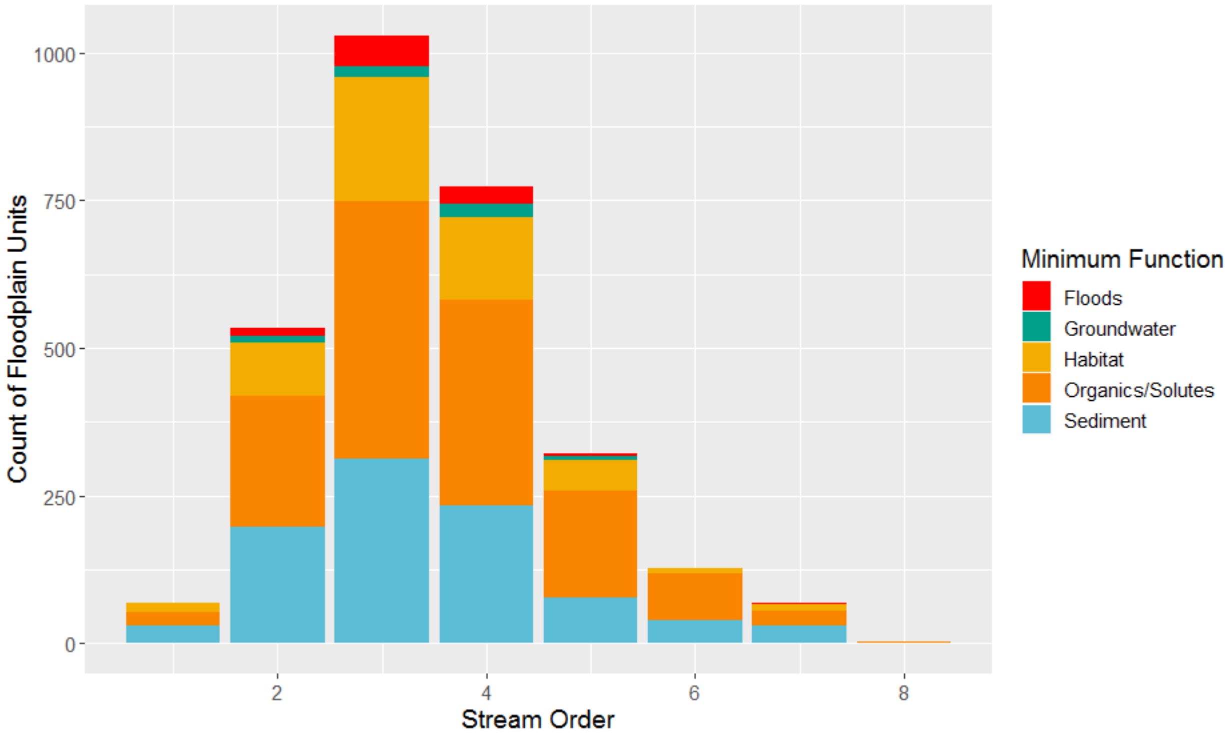
The figure below shows a histogram of the standard deviation of the five functional IFI values for each floodplain unit. The distribution of variation amongst functional IFI values is approximately normal.



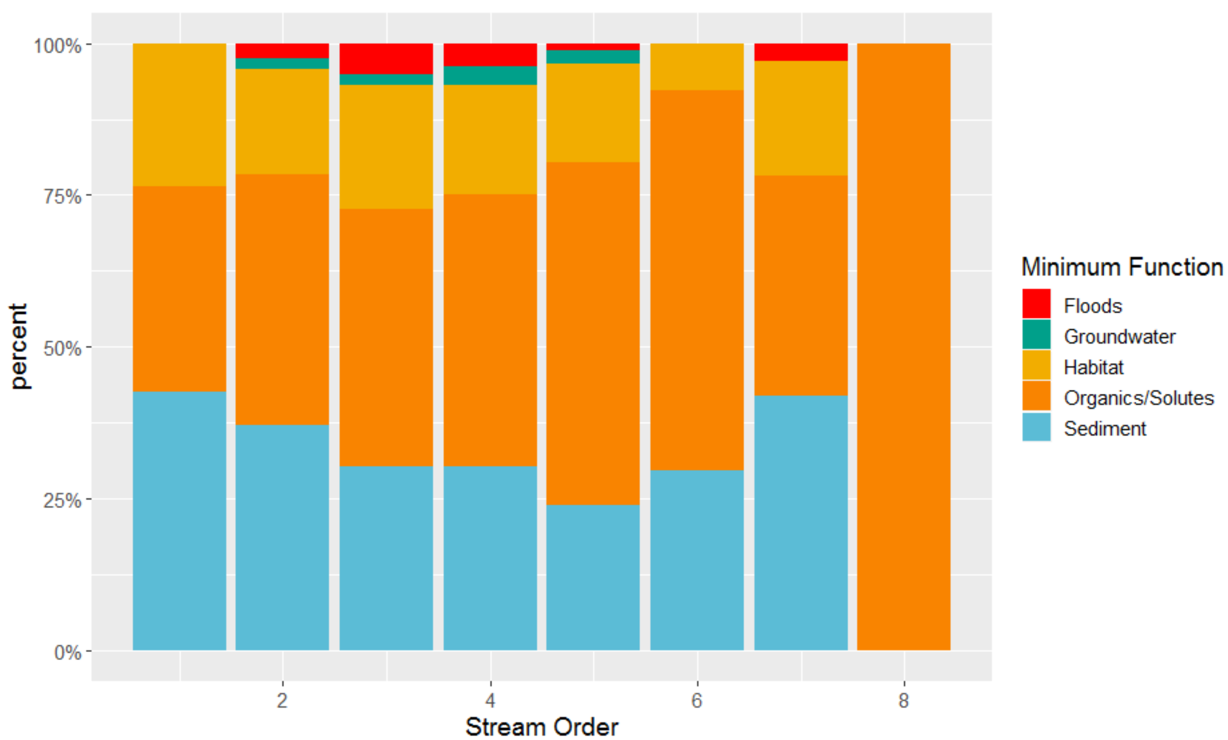
This analysis was repeated with floodplain units separated by stream order. It can be seen in the figure below that variability between functional IFI is higher for the higher order streams, though this relationship is not monotonically increasing.



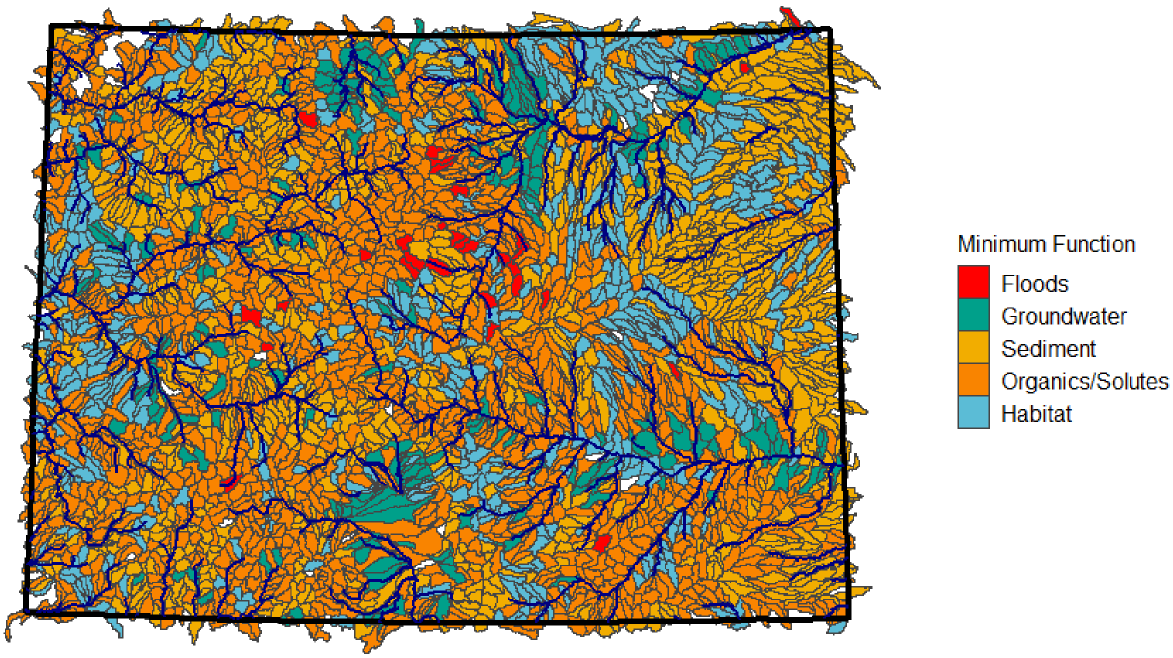
In addition to assessing the variability of the functional IFI, investigations were performed to understand the relative impact of the five functional IFI values on the overall IFI. The figure below shows the number of floodplain units by stream order for which a given function is lowest of the five.



The next figure shows the same distribution of minimum function by stream order, but with the distribution of minimum function expressed as the percentage of floodplain units for which a given function was the lowest of the five IFI values.

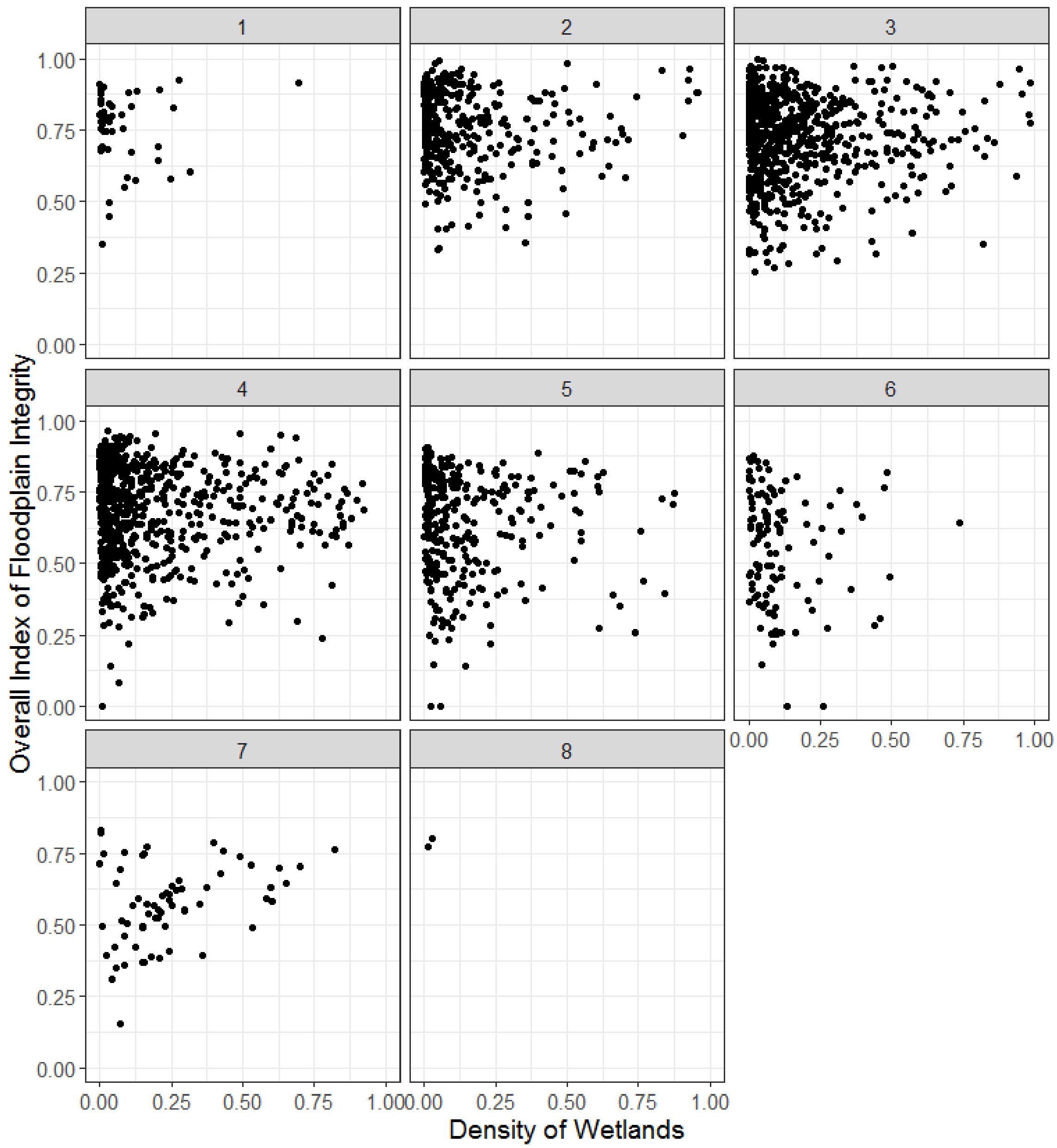


The map below shows the locations where a given function was the minimum function, with the color shown for the entire HUC-12 instead of the floodplain for visualization purposes.



10. IFI vs. wetland density by stream order

To further explore the relationship between wetland density and overall IFI, the regression was separated by stream order of the floodplain unit. The highest correlation coefficient when analyzed by stream order is 0.07 for seventh order floodplains (excluding eighth order which comprises only two floodplains). None of the regressions were significant.



Appendix B: Code

CONTENTS OF APPENDIX B

All code is available in a dynamic repository at *https://github.com/mnk5/floodplain_integrity.git*

1. *Calculation of shapefile stressor densities in floodplain*

The Python script Shapefile_Calculations.py was used to make the Arcpy tool “Shapefile Calculations” in the “Floodplain Integrity” toolbox. This script takes a folder of stressor shapefiles and a shapefile of the floodplain units and outputs stressor density as csv files in a nested folder.

Code:

```
#-------------------------------------------
#  Calculates density of shapefile per HUC-12
#
#-------------------------------------------

#Import system modules
import sys, string, os, arcpy, math, traceback, glob
import pandas as pd
import numpy
from arcpy.sa import *

# Allow output to overwrite...
arcpy.env.overwriteOutput = True

# Check out the ArcGIS Spatial Analyst extension license
arcpy.CheckOutExtension("Spatial")



try:


    #INPUT ARGUMENTS FOR GIS TOOL
    SHP_FLDR = arcpy.GetParameterAsText(0)        # Folder containing
shapefiles trimmed
    FP = arcpy.GetParameterAsText(1)              # FP intesected with
HUC-12 shapefile

#    #INPUT ARGUMENTS FOR PYTHON DIRECTLY
#    SHP_FLDR = "C:\Users\mnk5\Documents\GIS\DATA\Datasets_trimmed
      "      # Folder containing shapefiles trimmed
#    FP =
"C:\Users\mnk5\Documents\GIS\DATA\Datasets_trimmed\ForProcessing\

    #OUTPUTFOLDER
    Out_path= SHP_FLDR +"\\RESULTS"

    #Creating the new folder
    if not os.path.exists(Out_path):
        os.makedirs(Out_path)
```

```
    #GETTING FILES
    arcpy.AddMessage('')
    arcpy.AddMessage('-------------------------------------------')
    arcpy.AddMessage('ACCESSING SHAPEFILES')
    arcpy.AddMessage(' ')

    # Get area of FP by HUC-12
    arcpy.env.workspace = SHP_FLDR
    FILES = arcpy.ListFeatureClasses()

    arcpy.AddMessage('TABULATING FEATURE ABUNDANCE BY HUC-12')
    arcpy.AddMessage(' ')


    # write Floodplain area and HUC-12 identifier to Numpy Array
    HUC12_area = arcpy.da.FeatureClassToNumPyArray(FP,
["HUC12","FP_Areakm2"])
    # Convert Numpy array to Pandas dataframe (see
http://geospatialtraining.com/tutorial-creating-a-pandas-dataframe-
from-a-shapefile/)
    FP_df = pd.DataFrame(HUC12_area)
    FP_df.to_csv(Out_path + '\\FP_area.csv')
    FP_df = pd.read_csv(Out_path + '\\FP_area.csv') #don't know why
this has to be read back in from the file, but the merge doesn't work
otherwise.

    for fc in FILES:

        filename  = os.path.splitext(fc)[0]
#        arcpy.AddMessage(filename) # to test correct files are being
accessed

        # Trim to only floodplain extents and divide by HUC-12
        inFeatures = [fc, FP]
        arcpy.Intersect_analysis(inFeatures, Out_path +
"\\OutTrim.shp")
        desc = arcpy.Describe(fc)

        # Location to save files
        OutTrim = Out_path + "\\OutTrim.shp"
        OutTable = Out_path + "\\" + filename + "_table.csv"

        if desc.shapeType == "Point":
#        # add column of count per huc 12
            arcpy.Statistics_analysis(OutTrim, OutTable,
[["FID","COUNT"]], "HUC12")

        # Calculate density of points as number/ km^2 per HUC-12 and
add to csv
            df = pd.read_csv(OutTable)
            # merge tables of HUC-12 FP area and objects, keeping all
HUC-12 entries that have a feature in them
```

```
            df_results = df.merge(FP_df, on = "HUC12", how='left')
            df_results['Point_Density'] =
df_results['COUNT_FID']/df_results['FP_Areakm2']
            df_results.to_csv(OutTable)


        elif desc.ShapeType == "Polyline":

        # Calculate length of trimmed lines
            arcpy.AddField_management(OutTrim,"Length_km", "FLOAT")
            arcpy.CalculateField_management(OutTrim, "Length_km",
"!shape.length@kilometers!", "PYTHON", "#" )

        # Save sum of length by HUC-12
            arcpy.Statistics_analysis(OutTrim, OutTable,
[["Length_km","SUM"]], "HUC12")

        # Calculate density of lines as km/ km^2 per HUC-12 and add to
csv
            df = pd.read_csv(OutTable)
            # merge tables of HUC-12 FP area and objects, keeping all
HUC-12 entries that have a feature in them
            df_results = df.merge(FP_df, on = "HUC12", how='left')
            df_results['Line_Density'] =
df_results['SUM_Length_km']/df_results['FP_Areakm2']
            df_results.to_csv(OutTable)


        else: # for polygons

        # Calculate area of trimmed polygons
            arcpy.AddField_management(OutTrim,"area_km2", "FLOAT")
            arcpy.CalculateField_management(OutTrim, "area_km2",
"!shape.area@squarekilometers!", "PYTHON", "#" )
        # Save sum of area by HUC-12
            arcpy.Statistics_analysis(OutTrim, OutTable,
[["area_km2","SUM"]], "HUC12")

        # Calculate density of area per HUC-12 and add to csv
            df = pd.read_csv(OutTable)
            # merge tables of HUC-12 FP area and objects, keeping all
HUC-12 entries that have a feature in them
            df_results = df.merge(FP_df, on = "HUC12", how='left')
            df_results['Area_Density'] =
df_results['SUM_area_km2']/df_results['FP_Areakm2']
            df_results.to_csv(OutTable)


    arcpy.AddMessage(' ')
    arcpy.AddMessage('FLOODPLAIN PREPROCESSING  COMPLETED!')
except:
```

```
arcpy.AddError(arcpy.GetMessages())
arcpy.AddMessage(traceback.format_exc())
```

2. Hydrologic alteration aggregation calculations

This Python script, HydAlterationCalculations.py, takes the attributes of the stream lines with hydrologic alteration metrics associated and provides an aggregated value for each HUC-12 weighted either by the length or the stream order of the stream lines. The aggregated values are saved as csv files.

Code:

```
# -*- coding: utf-8 -*-
"""
Created on Wed Jan 16 09:28:54 2019

@author: mnk5
"""

import pandas as pd


## calculating hydrologic alteration methods with various weightings

attributefile =
"C:\\Users\\mnk5\\Documents\\GIS\DATA\\Hyd_Alteration\\ByHUC12\\attrib
utetable.txt"

df = pd.read_table(attributefile, delimiter=",")

hydfields = ["pnMH20", "pnFH1", "pnFH6", "pnFH7", "pnDH1",
"pnDH2","pnDH3","pnDH4","pnDH5","pnDH15" ]

df_hydalt = df[hydfields]


# Weight by length

df_lengthweight = df_hydalt.multiply(df["Length_km"], axis="index")

df_lengthweight["HUC12"] = df["HUC12"]

df_lengthsum = df.groupby('HUC12')['Length_km'].sum()
df_HA_byLength = df_lengthweight.groupby('HUC12').sum()

df_HA_byLength = df_HA_byLength.divide(df_lengthsum, axis="index")


# Weight by Stream Order

df_SOweight = df_hydalt.multiply(df["StrmOrder"], axis="index")
```

```
df_SOweight["HUC12"] = df["HUC12"]

df_SOsum = df.groupby('HUC12')['StrmOrder'].sum()
df_HA_bySO = df_SOweight.groupby('HUC12').sum()

df_HA_bySO = df_HA_bySO.divide(df_SOsum, axis="index")

# Calc max and avg

df_hydalt["HUC12"] = df["HUC12"]

df_maxHA = df_hydalt.groupby('HUC12').max()
df_meanHA = df_hydalt.groupby('HUC12').mean()

# save files to csv to use with GIS

df_HA_byLength.to_csv("C:\\Users\\mnk5\\Documents\\GIS\DATA\\Hyd_Alter
ation\\ByHUC12\\LengthWeightbyHUC12.csv")
df_HA_bySO.to_csv("C:\\Users\\mnk5\\Documents\\GIS\DATA\\Hyd_Alteratio
n\\ByHUC12\\SOWeightbyHUC12.csv")
```

3. Compilation and correlation analysis of stressor data

This R script, CorrelationAnalysis.R, takes the stressor densities from the csv files produced by Shapefile_calculations.py and raster processing and combines them into a single data table. The code outputs this merged data as a csv file. A correlation analysis is then performed, with the correlation matrix saved as a jpeg image.

Code:

```
#####################
# Floodplain Integrity Assessment
# Stressor data correlation analysis
# M. Karpack, Spring 2019


# Code to take all data tables from GIS data exports and assimilate
# And then check for correllation using Pearson's correlation
coeffcient

library(lsmeans)
library(corrplot)
library(foreign)
library(tools)
library(data.table)
library(RColorBrewer)

basepath <- "C:/Users/mnk5/Documents/floodplain_integrity"

# Load all csv files in folder into list
data.path <- paste(basepath, "/RawData/StressorData/", sep="")
filelist <- list.files(path = data.path, pattern="*.csv")

# read in each .csv file in folder and create a data frame with the
same name as the .csv file
for (i in 1:length(filelist)){

  assign(file_path_sans_ext(filelist[i]),
         read.csv(paste(data.path, filelist[i], sep=''))
  )}

## Get all information relevant into one df using FP HUC-12 as basis

data.merge <- merge(FP_Info[,c("HUC12", "FP_Areakm2", "StrmOrder")],
AgricultureArea[, c("HUC12", "MEAN")], by = "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="MEAN"] <- "Agriculture"

data.merge <- merge(data.merge, Buildings[, c("HUC12",
"Area_Density")], by = "HUC12", all.x = TRUE)
```

```
colnames(data.merge)[colnames(data.merge)=="Area_Density"] <-
"Buildings"

data.merge <- merge(data.merge, CanalDitch[, c("HUC12",
"Line_Density")], by = "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="Line_Density"] <-
"Ditches"

data.merge <- merge(data.merge, DevelopedArea[, c("HUC12", "MEAN")],
by = "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="MEAN"] <- "Developed"

data.merge <- merge(data.merge, ForestLoss[, c("HUC12", "MEAN")], by =
"HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="MEAN"] <- "ForestLoss"

data.merge <- merge(data.merge, ImperviousArea[, c("HUC12", "MEAN")],
by = "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="MEAN"] <- "Impervious"

data.merge <- merge(data.merge, LeveedArea[, c("HUC12",
"Area_Density")], by = "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="Area_Density"] <-
"LeveedArea"

data.merge <- merge(data.merge, NonNativeVeg[, c("HUC12", "MEAN")], by
= "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="MEAN"] <- "NonNativeVeg"

data.merge <- merge(data.merge, RoadsRailroads[, c("HUC12",
"Line_Density")], by = "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="Line_Density"] <-
"Roads_Rail"

data.merge <- merge(data.merge, WellStructures[, c("HUC12",
"Point_Density")], by = "HUC12", all.x = TRUE)
colnames(data.merge)[colnames(data.merge)=="Point_Density"] <- "Wells"

data.merge <- merge(data.merge, MeanHA_MaxOrderOnly[, c("HUC12",
"MEAN_pnMH20", "MEAN_pnFH1","MEAN_pnFH6",

"MEAN_pnFH7","MEAN_pnDH1", "MEAN_pnDH2","MEAN_pnDH3",
                                                        "MEAN_pnDH4",
"MEAN_pnDH5","MEAN_pnDH15")], by = "HUC12", all.x = TRUE)
setnames(data.merge, old =c("MEAN_pnMH20", "MEAN_pnFH1","MEAN_pnFH6",
"MEAN_pnFH7","MEAN_pnDH1", "MEAN_pnDH2","MEAN_pnDH3",
                            "MEAN_pnDH4", "MEAN_pnDH5","MEAN_pnDH15"
), new = c("MH20", "FH1", "FH6","FH7", "DH1", "DH2",

"DH3","DH4","DH5","DH15" ))
```

```
## Version with zeros changed to NA
data.merge.NA <- data.merge
data.merge.NA[data.merge.NA==0] <- NA

# version with NA changed to zero
data.merge[is.na(data.merge)] <- 0


# Save as .csv file
out.path <- paste(basepath, "/Outputs/", sep="")
out.file <- paste(out.path, "Combined_Data.csv", sep="")
write.csv(data.merge, file = out.file, row.names = FALSE)


##########################################################

# Correlation analysis (omitting NAs)
Correl.NA <- cor(data.merge.NA[,4:length(data.merge.NA)], use =
"pairwise.complete.obs")

# Significance test
res.NA <- cor.mtest(data.merge.NA[,4:length(data.merge.NA)],
conf.level =0.95)

# Plotting (and saving) correlations
out.graph.NA <- paste(out.path, "Correlation_NA.jpg", sep="")
jpeg(out.graph.NA, width = 2000, height = 2000, units = "px")
corrplot(Correl.NA, type = "upper", method = "color", tl.col="black",
tl.srt=45,
         tl.cex= 2.5, diag=FALSE, addCoef.col = "#9fa0a5",number.cex =
2, cl.pos ="n")
dev.off()


# Correlation analysis (w zero instead of NA)
Correl <- cor(data.merge[,4:length(data.merge)], use =
"pairwise.complete.obs")

# Significance test
res <- cor.mtest(data.merge[,4:length(data.merge)], conf.level =0.95)

# Plotting (and saving) correlations
out.graph <- paste(out.path, "Correlation.jpg", sep="")
jpeg(out.graph, width = 2000, height = 2000, units = "px")
corrplot(Correl, type = "upper", method = "color", tl.col="black",
tl.srt=45,
         tl.cex= 2.5, diag=FALSE, addCoef.col = "#9fa0a5", number.cex
= 2, cl.pos ="n")
dev.off()
```

4. Calculation of IFI

This R script, IndexCalcualtion.R, takes the csv of the stressor density data output from CorrelationAnalysis.R and rescales the stressor data, computes the five functional IFI values and the overall IFI. Various plots are also created to show results. The resultant IFI values are output as a csv file.

Code:

```
#####################
# Floodplain Integrity Assessment
# Index Calculation for functions
# M. Karpack, Spring 2019

# Take assembled stressor data and translate to 0 to 1 metrics
# for individual floodplain functions

library(ggplot2)
library(RColorBrewer)
library(corrplot)
library(emmeans)
library(psych)


# set path to Git folder
basepath <- "C:/Users/mnk5/Documents/floodplain_integrity"
out.path <- paste(basepath, "/Outputs/", sep="") # for saving outputss

# Load csv file of stressor data from "CorrelationAnalysis.R" script
output
data.path <- paste(basepath, "/Outputs/Combined_Data.csv", sep="")
all.data <- read.csv(data.path)
data.names <- colnames(all.data)

# Convert HUC-12 from numeric to character
all.data$HUC12 <- as.character(all.data$HUC12)

# boxplots to look at range of data

for (i in 4:ncol(all.data)){
  hist(all.data[,i], main = data.names[i])
  boxplot(all.data[,i], main = data.names[i])
  text(y=fivenum(all.data[,i]), labels = round(fivenum(all.data[,i]),
digits = 2), x = 0.75)

}

#####################
```

```
# Get only final stressors and HUC-12 Identifier into df

keep.columns <- c("Agriculture", "Buildings", "Ditches", "Developed", 
"ForestLoss",
                  "Impervious", "LeveedArea", "NonNativeVeg", 
"Roads_Rail","Wells", "MH20")
stressors <- all.data[, keep.columns]

# adjust stressors that are not 0 to 1
stressors$Impervious <- stressors$Impervious/100 # convert percent to 
decimal

# Scale count and line denisty by max value observed
stressors$Ditches <- stressors$Ditches/max(stressors$Ditches)
stressors$Roads_Rail <- stressors$Roads_Rail/max(stressors$Roads_Rail)
stressors$Wells <- stressors$Wells/max(stressors$Wells)


# Compare all measures
boxplot(stressors, use.cols = TRUE, ylab = 'Stressor Density')


# Scale buildings to max building density in CO
stressors$Buildings <- stressors$Buildings/max(stressors$Buildings)


# Make neagtive
stressors.neg <- 1-stressors
# boxplot(stressors.neg, use.cols = T)

#####################
# Calculate functions as average of stressors

# choose datasets by function

# Flood reduction
FR.stressors <- c("Buildings", "Roads_Rail", "ForestLoss", 
"Developed", "LeveedArea")
# Groundwater regulation
GW.stressors <- c("Impervious", "Ditches", "Agriculture", 
"ForestLoss", "Wells")
# Sediment Flux
SF.stressors <- c("MH20", "Agriculture", "Roads_Rail", "ForestLoss")
# Organics and Solute regulation
OS.stressors <- c("MH20", "ForestLoss", "Impervious") # Roads_Rail not 
included b/c of high correlation
# Habitat provisioning
HP.stressors <- c("Roads_Rail", "MH20", "NonNativeVeg", "Developed", 
"Agriculture", "ForestLoss")

data.byfunction <- list(FR.stressors, GW.stressors, SF.stressors, 
OS.stressors, HP.stressors)
```

```
# Compute Index as average of stressors for each function
Function.Index <- data.frame(matrix(NA, nrow = nrow(stressors.neg),
ncol = length(data.byfunction)))

for (i in 1:length(data.byfunction)) {
  Function.Index[,i] <- rowMeans(stressors.neg[,data.byfunction[[i]]])
}

colnames(Function.Index) <- c("Floods", "Groundwater", "Sediment",
                              "Organics/Solutes", "Habitat")


# plot boxplot of index by function
function.plot <- ggplot(stack(Function.Index), aes(x = ind, y =
values)) +
  geom_boxplot() +
  scale_y_continuous(limits = c(0,1)) +
  xlab("Floodplain Function") +
  ylab("Integrity Index") +
  ggtitle("Index of Floodplain Integrity by Function")
function.plot

# plot correlation of Indices

function.cor <- cor(Function.Index, use = "pairwise.complete.obs")

out.graph <- paste(out.path, "IFI_Correlation.jpg", sep="")
jpeg(out.graph, width = 2000, height = 2000, units = "px")
corrplot(function.cor, type = "upper", method = "circle",
tl.col="black", tl.srt=45,
         tl.cex= 4.5, diag=FALSE, addCoef.col = "#bbbcc1", number.cex
= 4, cl.pos ="n")
dev.off()



# Compute overall Index of floodplain Integrity
IFI <- data.frame(IFI.geomean = apply(Function.Index, 1, prod)^(1/5))
IFI.product <- data.frame(IFI.prod = apply(Function.Index, 1, prod))
IFI.comb <- data.frame(IFI,IFI.product)

IFI.plot <- ggplot(stack(IFI.comb), aes(x = ind, y = values)) +
  scale_y_continuous(limits = c(0,1)) +
  geom_boxplot() +
  xlab("") +
  ylab("Index of Floodplain Integrity")

IFI.plot

###################################
```

```
# GEO MEAN

# Compute index using geometric mean
Function.Index.Geo <- data.frame(matrix(NA, nrow =
nrow(stressors.neg), ncol = length(data.byfunction)))

for (i in 1:length(data.byfunction)) {
  Function.Index.Geo[,i] <-
apply(stressors.neg[,data.byfunction[[i]]], 1, function(x)
geometric.mean(x))
}

colnames(Function.Index.Geo) <- c("Floods", "Groundwater", "Sediment",
                              "Organics/Solutes", "Habitat")



# plot boxplot of index by function with geomean
function.plot.geo <- ggplot(stack(Function.Index.Geo), aes(x = ind, y
= values)) +
  geom_boxplot() +
  scale_y_continuous(limits = c(0,1)) +
  xlab("Floodplain Function") +
  ylab("Integrity Index") +
  ggtitle("Index of Floodplain Integrity by Function, Geometric Mean")
function.plot.geo

# Compute overall Index of floodplain Integrity with Geo Mean
IFI.geo <- data.frame(IFI.geomean = apply(Function.Index.Geo, 1,
prod)^(1/5))
IFI.product.geo <- data.frame(IFI.prod = apply(Function.Index.Geo, 1,
prod))
IFI.comb.geo <- data.frame(IFI.geo,IFI.product.geo)

IFI.plot.geo <- ggplot(stack(IFI.comb.geo), aes(x = ind, y = values))
+
  scale_y_continuous(limits = c(0,1)) +
  geom_boxplot() +
  xlab("") +
  ylab("Index of Floodplain Integrity, Function Geometric Mean")

IFI.plot.geo

###########################
# Cap stressors at 75th percentile

stressors.scaled <- stressors # initialize vector
percent.capped <- list()

# loop over stressors
for (i in 1:ncol(stressors)) {
  # find 90th percentile
```

```
  limit <- quantile(stressors[,i], probs = 0.90)

  # for non-zero 90th percentiles, compute as relative to 90th
percentile
  if (limit != 0) {
    stressors.scaled[,i] <- stressors.scaled[,i]/limit

    # Count percentage of data being capped to one
    percent.capped[[i]] <-
sum(stressors.scaled[,i]>1)/nrow(stressors.scaled)

    # set values over 90th percentile to 1
    stressors.scaled[,i][stressors.scaled[,i]>1] <- 1

  } else {
    # if 90th percentile is 0, scale relative to max value
    stressors.scaled[,i] <-
stressors.scaled[,i]/max(stressors.scaled[,i])

    percent.capped[[i]] <- 0
  }

}

## Boxplot scaled stressors
boxplot(stressors.scaled, use.cols = TRUE, ylab = 'Scaled Stressor
Density')


# Compute  Index as average of stressors scaled for each function
Function.Index.Scaled <- data.frame(matrix(NA, nrow =
nrow(stressors.scaled), ncol = length(data.byfunction)))

for (i in 1:length(data.byfunction)) {
  Function.Index.Scaled[,i] <- 1 -
rowMeans(stressors.scaled[,data.byfunction[[i]]])
}

colnames(Function.Index.Scaled) <- c("Floods", "Groundwater",
"Sediment",
                              "Organics/Solutes", "Habitat")


# plot boxplot of index by function
function.plot.scaled <- ggplot(stack(Function.Index.Scaled), aes(x =
ind, y = values)) +
  geom_boxplot() +
  scale_y_continuous(limits = c(0,1)) +
  xlab("Floodplain Function") +
  ylab("Integrity Index") +
  ggtitle("Index of Floodplain Integrity by Function, Scaled
Stressors")
```

```
function.plot.scaled

# plot correlation of Indices

function.scaled.cor <- cor(Function.Index.Scaled, use =
"pairwise.complete.obs")

out.graph <- paste(out.path, "IFI_Scaled_Correlation.jpg", sep="")
jpeg(out.graph, width = 2000, height = 2000, units = "px")
corrplot(function.scaled.cor, type = "upper", method = "circle",
tl.col="black", tl.srt=45,
         tl.cex= 4.5, diag=FALSE, addCoef.col = "#bbbcc1", number.cex
= 4, cl.pos ="n")
dev.off()



# Compute overall Index of floodplain Integrity
IFI.scaled <- data.frame(IFI.geomean = apply(Function.Index.Scaled, 1,
function(x) geometric.mean(x)))
IFI.product.scaled <- data.frame(IFI.prod =
apply(Function.Index.Scaled, 1, prod))
IFI.comb.scaled <- data.frame(IFI.scaled,IFI.product.scaled)

IFI.scaled.plot <- ggplot(stack(IFI.comb.scaled), aes(x = ind, y =
values)) +
  scale_y_continuous(limits = c(0,1)) +
  geom_boxplot() +
  xlab("") +
  ylab("Index of Floodplain Integrity, scaled stressors")

IFI.scaled.plot

# Export to csv
HUC12 <- all.data$HUC12

combined.data <-
data.frame(HUC12,Function.Index.Scaled,IFI.comb.scaled)
IFI.outfile <- paste(out.path, "IFI_Scaled.csv", sep="")
write.csv(combined.data, file = IFI.outfile)
```

5. Analysis of IFI values

This R script, IndexAnalysis.R, uses the IFI values calculated in IndexCalculation.R and associated with several spatial attributes in GIS to perform a variety of analyses on the results. IFI values are analyzed for correlation, spatially, for sensitivity and variability, and relationship with other river health metrics. Outputs are primarily graphical.

Code:

```
#####################
# Floodplain Integrity Assessment
# Index Analysis
# M. Karpack, Spring 2019

# Analysis IFI data by stream order, floodplain area, ecoregion and
city/not city,
# Comparison to IFI and identification of most impacted function.

library(ggplot2)
library(RColorBrewer)
library(wesanderson)
library(tidyr)
library(grid)
library(gridExtra)
library(emmeans)
library(scales)
library(dplyr)
library(data.table)
library(stringr)
library(psych)
library(ggpubr)


# set path to Git folder
basepath <- "C:/Users/mnk5/Documents/floodplain_integrity"
out.path <- paste(basepath, "/Outputs/", sep="") # for saving outputss

# Load csv file of stressor data with Ecoregion and city as exported
from GIS
data.path <- paste(basepath, "/RawData/IFI_Ecoregion_cities.csv",
sep="")
all.data <- read.csv(data.path)
colnames(all.data)[which(names(all.data) == "IFI_geomea")] <-
"IFI_geomean"

col.names <- colnames(all.data)

# find columns to plot
```

```
functions <- c("Floods", "Groundwate", "Sediment", "Organics_S",
"Habitat")
func.IFI <- all.data[, functions]
colnames(func.IFI) <- c("Floods", "Groundwater", "Sediment",
"Organics_Solutes", "Habitat")

# colnames(func.IFI)[which(names(func.IFI) == "IFI_geomean")] <-
"Overall IFI"

######################################
# general statistics about overall IFI
IFI.stats <- describe(all.data$IFI_geomean)
IFI.stats

IFI.func.stats <- apply(func.IFI, 2, function(x) describe(x))
IFI.func.stats

######################################
# Histograms of IFI results

p <- ggplot(gather(func.IFI), aes(value)) +
  geom_histogram(bins = 20) +
  facet_wrap(~key, scales = 'free_y') +
  xlab("Index of Floodplain Integrity") +
  ylab("Count") +
  theme(text = element_text(size=20))
p

b <- ggplot(all.data, aes(x=IFI_geomean)) +
  geom_histogram(bins = 20) +
  xlab("Overall Index of Floodplain Integrity" ) +
  ylab("Count") +
  theme(text = element_text(size=20))
b

#######################################
# Plot bar graphs of function IFI by area

# Arrange data into groups of 0.05 bins
breaks <- seq(0.00, 1, 0.05)
breaks[1] <- -Inf

by.area<- data.frame(Area_km2 = all.data$FP_Areakm2)

by.area$Floods <- cut(func.IFI$Floods, breaks)
by.area$Groundwater <- cut(func.IFI$Groundwater, breaks)
by.area$Sediment <- cut(func.IFI$Sediment, breaks)
by.area$Organics_Solutes <- cut(func.IFI$Organics_Solutes, breaks)
by.area$Habitat <- cut(func.IFI$Habitat, breaks)
by.area$Overall_IFI <- cut(all.data$IFI_geomean, breaks)

Flood.sum <- by.area %>%
```

```
  group_by(Floods) %>%
  summarise(area = sum(Area_km2))

GW.sum <- by.area %>%
  group_by(Groundwater) %>%
  summarise(area = sum(Area_km2))

Sed.sum <- by.area %>%
  group_by(Sediment) %>%
  summarise(area = sum(Area_km2))

OS.sum <- by.area %>%
  group_by(Organics_Solutes) %>%
  summarise(area = sum(Area_km2))

Habitat.sum <- by.area %>%
  group_by(Habitat) %>%
  summarise(area = sum(Area_km2))

Overall.sum <- by.area %>%
  group_by(Overall_IFI) %>%
  summarise(area = sum(Area_km2))


# THIS IS ALL MANUAL AND WILL NEED TO CHANGE IF DATA CHANGES
area.sum <- data.frame(breaks = OS.sum$Organics_Solutes)
area.sum$Floods <- NA
area.sum[4:20,2] <- Flood.sum$area
area.sum$Groundwater <- NA
area.sum[6:20,3] <- GW.sum$area
area.sum$Sediment <- NA
area.sum[2:20,4] <- Sed.sum$area
area.sum$Organics_Solutes <- OS.sum$area
area.sum$Habitat <- NA
area.sum[4:20,6] <- Habitat.sum$area
area.sum$Overall <- Overall.sum$area

area.sum$breaks <- as.numeric(area.sum$breaks)

# Graph with facet wrap "histograms"

area.df <- melt(area.sum, id = 1, measure = 2:7)
levels(area.df$variable) = c("Flood Reduction", "Groundwater Storage", 
"Sediment Regulation",
                          "Organics/Solutes Regulation", "Habitat 
Provision", "Overall IFI")

area.barplot <- ggplot(data = na.omit(area.df), aes(x = breaks, y = 
value)) +
  geom_bar(stat = "identity", width = 1,  position = position_nudge(x 
= -0.5), fill = "grey27") +
  scale_x_continuous(limits = c(0, 20), breaks = seq(0, 20, 4),
```

```
                     labels = c("0", "0.2", "0.4", "0.6", "0.8",
"1.0")) +
  facet_wrap(~ variable, ncol = 3) +
  labs(x = "IFI Value", y = bquote("Total floodplain area, " ~km^2)) +
  theme_bw(base_size = 16) +
  theme(strip.background =element_rect(fill="grey93"))
area.barplot


#######################################
# Plot by floodplain area
a1 <- ggplot(all.data, aes(x = FP_Areakm2, y = Floods)) +
    geom_point() +
    scale_x_log10(labels = trans_format('log10',math_format(10^.x))) +
    scale_y_continuous() +
    xlab("") +
    ylab("Floods IFI") +
    theme_bw()

a2 <- ggplot(all.data, aes(x = FP_Areakm2, y = Groundwate)) +
  geom_point() +
  scale_x_log10(labels = trans_format('log10',math_format(10^.x))) +
  scale_y_continuous() +
  xlab("") +
  ylab("Groundwater IFI") +
  theme_bw()

a3 <- ggplot(all.data, aes(x = FP_Areakm2, y = Sediment)) +
  geom_point() +
  scale_x_log10(labels = trans_format('log10',math_format(10^.x))) +
  scale_y_continuous() +
  xlab(bquote("Floodplain unit area," ~km^2)) +
  ylab("Sediment IFI") +
  theme_bw()

a4 <- ggplot(all.data, aes(x = FP_Areakm2, y = Organics_S)) +
  geom_point() +
  scale_x_log10(labels = trans_format('log10',math_format(10^.x))) +
  scale_y_continuous() +
  xlab(bquote("Floodplain unit area," ~km^2)) +
  ylab("Organics and Solutes IFI") +
  theme_bw()

a5 <- ggplot(all.data, aes(x = FP_Areakm2, y = Habitat)) +
  geom_point() +
  scale_x_log10(labels = trans_format('log10',math_format(10^.x))) +
  scale_y_continuous() +
  xlab(bquote("Floodplain unit area," ~km^2)) +
  ylab("Habitat IFI") +
  theme_bw()

grid.arrange(a1, a2, a5, a4, a3, nrow = 2)
```

```
# Linear relationship between IFI as function of Area
area.lm <- lm(all.data$IFI_geomean ~ log10(all.data$FP_Areakm2))
R2 <- summary(area.lm)$r.squared
summary(area.lm)
cor.test(all.data$FP_Areakm2, all.data$IFI_geomean, method =
c("pearson"))

a6 <- ggplot(all.data, aes(x = FP_Areakm2, y = IFI_geomean)) +
  geom_point() +
  scale_x_log10(labels = trans_format('log10',math_format(10^.x))) +
  scale_y_continuous() +
  xlab(bquote("Floodplain unit area," ~km^2)) +
  ylab("Overall IFI") +
  theme_bw() +
  theme(text = element_text(size=20))
a6



############################
# IFI by stream order
all.data[all.data == -999] <- NA
count.data <- as.data.frame((table(all.data$StrmOrder)))
names(count.data)[1] = 'StrmOrder'
count.data$Freq <- paste(" N =", as.character(count.data$Freq), sep =
" ")

SO_comparisons <- list( c("1","2"), c("2","3"), c("3", "4"),
c("4","5"), c("5","6"), c("6", "7"))

SO <- ggplot(na.omit(all.data), aes(StrmOrder, IFI_geomean, group =
StrmOrder)) +
  geom_boxplot(na.rm = TRUE) +
  scale_x_discrete(name = "Stream Order", breaks = seq(1:8)) +
  scale_y_continuous(limits = c(0,1.5)) +
  ylab("Overall IFI") +
  theme_linedraw() +
  theme(text = element_text(size=16), panel.grid.major.x =
element_blank(), panel.grid.major.y = element_blank(),
        panel.grid.minor.y = element_blank()) +
  geom_text(data = count.data, aes(StrmOrder, y = 1.05, label = Freq),
nudge_y = 0.05, size = 4) +
  labs(tag = "c)") +
  stat_compare_means(comparisons = SO_comparisons, label = "p.signif",
method = "t.test",
                     label.y = seq(1.25, 1.45,
0.2/length(SO_comparisons)))

SO

# Test for significant difference
```

```
all.data$StrmOrder <- as.factor(all.data$StrmOrder)
SO.lm <- lm(IFI_geomean ~ StrmOrder, data = all.data)
SO.pairwise <- lsmeans(SO.lm, pairwise ~ StrmOrder)
method.contrasts <- SO.pairwise$contrasts
method.contrasts
# Results - 1-3 not sig different, 4-6 all sig different fromnext
larger, 6-7 not sig different, 8 is weird.

############################
# IFI by ecoregion

all.data$ECO_name <- as.factor(all.data$ECO_name)

# get counts for label
count.data.ECO <- as.data.frame((table(all.data$ECO_name)))
names(count.data.ECO)[1] = 'ECO_name'
count.data.ECO$Freq <- paste(" N =",
as.character(count.data.ECO$Freq), sep = " ")

# Compute ANOVA
eco.aov <- aov(IFI_geomean ~ ECO_name, data = all.data)
summary(eco.aov)
# result: they are significantly different

eco.lm <- lm(IFI_geomean ~ ECO_name, data = all.data)
eco.pairwise <- lsmeans(eco.lm, pairwise ~ ECO_name)
method.contrasts <- eco.pairwise$contrasts
method.contrasts
# Results - three statistically significant groups

# add column for coloring in ggplot
all.data$sig.group <- NA
all.data$sig.group <- ifelse(all.data$ECO_name %in% c('ANP', 'COP',
'SRO'), 'A',
                             ifelse(all.data$ECO_name %in% c('HPL',
'WYB'), 'B', 'C'))

ECO <- ggplot(all.data, aes(ECO_name, IFI_geomean)) +
  geom_boxplot(aes(ECO_name, IFI_geomean, fill = sig.group)) +
  scale_fill_manual(values = c("#217463","#32ae95", "#9ce3d4")) +
  scale_x_discrete(name = "\nEPA Ecoregion, Level 3") +
  ylab("Overall IFI\n") +
  theme(text = element_text(size=20), panel.grid.major.x =
element_blank(),
        legend.position = "none") +
  geom_text(data = count.data.ECO, aes(ECO_name, y = 1.05, label =
Freq), nudge_y = 0.05, size = 5)
ECO

#############################
# IFI by city or not
```

```
all.data$In_City <- as.factor(all.data$In_City)

# get counts for label
count.data.city <- as.data.frame((table(all.data$In_City)))
names(count.data.city)[1] = 'In_City'
count.data.city$Freq <- paste(" N =",
as.character(count.data.city$Freq), sep = " ")

# T test for difference
t.test(IFI_geomean ~ In_City, data = all.data)
# result: means are not equal

city_comparisons <- list(c("0", "1"))

City.plot <- ggplot(all.data, aes(In_City, IFI_geomean)) +
  geom_boxplot(aes(In_City, IFI_geomean)) +
  scale_x_discrete(name = "", labels = c("Rural", "Urban")) +
  scale_y_continuous(limits = c(0,1.5)) +
  ylab("Overall IFI") +
  theme_linedraw() +
  theme(text = element_text(size=16), panel.grid.major.x =
element_blank(), panel.grid.major.y = element_blank(),
        panel.grid.minor.y = element_blank(), legend.position =
"none") +
  geom_text(data = count.data.city, aes(In_City, y = 1.05, label =
Freq), nudge_y = 0.05, size = 4) +
  labs(tag = "b)") +
  stat_compare_means(comparisons = city_comparisons, label =
"p.signif",
                    label.y = c(1.25))
City.plot

# Summary statistics, urban vs rural
all.data %>% group_by(In_City) %>% summarize(mean = mean(IFI_geomean),
med = median(IFI_geomean))

##############################
# IFI by Physiographic region

# Convert to factor and re-order to match geography
all.data$PhysioReg <- factor(all.data$PhysioReg,
                                levels = c("Intermontane Plateaus",
"Rocky Mountain System", "Interior Plains"),
                                ordered = TRUE)

# get counts for label
count.data.phys <- as.data.frame((table(all.data$PhysioReg)))
names(count.data.phys)[1] = 'PhysioReg'
count.data.phys$Freq <- paste(" N =",
as.character(count.data.phys$Freq), sep = " ")

# Test for differences
```

```
phys.lm <- lm(IFI_geomean ~ PhysioReg, data = all.data)
phys.pairwise <- lsmeans(phys.lm, pairwise ~ PhysioReg)
method.contrasts <- phys.pairwise$contrasts
method.contrasts
# results: Interior plains different from both Rocky mtn and Plateaus

Phys_comparisons <- list(c("Intermontane Plateaus", "Rocky Mountain
System"),
                         c("Rocky Mountain System", "Interior
Plains"),
                         c("Intermontane Plateaus", "Interior
Plains"))

#Plot boxplots
PHYS <- ggplot(all.data, aes(PhysioReg, IFI_geomean)) +
  geom_boxplot(aes(PhysioReg, IFI_geomean)) +
  scale_x_discrete(name = NULL, labels = function(x) str_wrap(x, width
= 20)) +
  scale_y_continuous(limits = c(0,1.5)) +
  ylab("Overall IFI") +
  theme_linedraw() +
  theme(text = element_text(size=16), panel.grid.major.x =
element_blank(), panel.grid.major.y = element_blank(),
        panel.grid.minor.y = element_blank(), legend.position =
"none") +
  geom_text(data = count.data.phys, aes(PhysioReg, y = 1.05, label =
Freq), nudge_y = 0.05, size = 4) +
  labs(tag = "a)") +
  stat_compare_means(comparisons = Phys_comparisons, label =
"p.signif",
                     label.y = c(1.25, 1.35, 1.45))
PHYS

# Stream Order by physiographic region
phys.so <- ggplot(na.omit(all.data), aes(StrmOrder)) +
  geom_bar() +
  facet_wrap(~ PhysioReg) +
  xlab("Stream Order") +
  ylab("Number of Floodplain Units") +
  theme_bw() +
  theme(text = element_text(size = 16))
phys.so

# Summary statistics, physioregion
all.data %>% group_by(PhysioReg) %>% summarize(mean =
mean(IFI_geomean), med = median(IFI_geomean))

##############################
# Combine boxplots to make figure

# divide grid arrange by 5
Figure <- grid.arrange(PHYS, City.plot, SO,
```

```
                       layout_matrix = rbind(c(1,1,1,2,2),
c(3,3,3,3,3)))

##############################
# IFI vs ICI comparison

# read export from GIS
ICI <- read.csv(paste(basepath, "/RawData/ICI_byHUC12.csv", sep=""))
# read file intersected with the floodplain
ICI.intersect <- read.csv(paste(basepath,
"/RawData/ICI_byHUC12_FloodplainIntersect.csv", sep=""))

IFI <- func.IFI
IFI$Overall <- all.data$IFI_geomea
IFI$HUC12 <- all.data$HUC12

# Join ICI and IFI based on HUC12
ICI.comp <- merge(IFI, ICI, by.x = "HUC12", by.y = "IFI_HUC12", all.x
= TRUE)
names(ICI.comp)[names(ICI.comp)== 'MEAN_ICI_I'] <- "ICI"

ICI.intersect.comp <- merge(IFI, ICI.intersect, by.x = "HUC12", by.y =
"IFI_HUC12", all.x = TRUE)
names(ICI.intersect.comp)[names(ICI.intersect.comp)== 'MEAN_ICI_I'] <-
"ICI"

# fit linear models
ICI.lm <- lm(data = ICI.comp, Overall ~ ICI)
R2.ICI <- summary(ICI.lm)$r.squared

ICI.intersect.lm <- lm(data = ICI.intersect.comp, Overall ~ ICI)
R2.ICI.intersect <- summary(ICI.intersect.lm)$r.squared
cor.test(ICI.intersect.comp$ICI, ICI.intersect.comp$Overall, method =
c("pearson"))

summary(ICI.intersect.lm)

# Scatter plot of ICI vs IFI
ICI.plot <- ggplot(ICI.comp, aes(x = ICI, y = Overall)) + geom_point()
+
  xlim(0,1) + ylim(0,1) +
  coord_equal() +
  xlab("Index of Catchment Integrity") +
  ylab("Overall Index of Floodplain Integrity") +
  ggtitle("All Catchments") +
  geom_text(x= 0.1, y=0.1, label = paste0("R^2 = ", round(R2.ICI,2)))
+
  theme_bw()

# Scatter plot for catchments intersected with floodplains, ICI vs IFI
ICI.intersect.plot <- ggplot(ICI.intersect.comp, aes(x = ICI, y =
Overall)) +
```

```
  geom_point(size = 1) +
  xlim(0,1) + ylim(0,1) +
  coord_equal() +
  xlab("Index of Catchment Integrity") +
  ylab("Overall Index of Floodplain Integrity") +
  # geom_text(x= 0.1, y=0.1, label = paste0("R^2 = ",
round(R2.ICI.intersect,2))) +
  theme_bw() +
  theme(text = element_text(size=16)) +
  labs(tag = "a)")

grid.arrange(ICI.plot, ICI.intersect.plot, ncol = 2)


# Look at distribution of ICI values (very few over 0.8)
# hist(ICI.comp$ICI, xlim = c(0,1))

##########################################
# Compare IFI to wetland abundance

# read in wetland abundance by HUC-12 file
wetlands <- read.csv(paste(basepath, "/RawData/Wetlands_table.csv",
sep=""))
wetlands <- wetlands[,c("HUC12", "Area_Density")]

IFI$StrmOrder <- all.data$StrmOrder
IFI$StrmOrder <- as.factor(IFI$StrmOrder)

# Join Wetland abundance and IFI based on HUC12
wetlands.comp <- merge(wetlands, IFI, by = "HUC12")

# fit linear model
wetlands.lm <- lm(data = wetlands.comp, Overall ~ Area_Density)
R2.wetlands <- summary(wetlands.lm)$r.squared
summary(wetlands.lm)
cor.test(wetlands.comp$Area_Density, wetlands.comp$Overall, method =
c("pearson"))

# lm by stream order

wetlands.lm.order <- by(wetlands.comp, wetlands.comp$StrmOrder,
                        function(x) lm(data = x, Overall ~
Area_Density))
R2.wetlands.order <- lapply(wetlands.lm.order, function(x)
summary(x)$r.squared)


# Scatter plot of wetlands vs IFI
wetlands.plot <- ggplot(wetlands.comp, aes(x = Area_Density, y =
Overall)) +
  geom_point(size = 1) +
  xlim(0,1) + ylim(0,1) +
```

```
  coord_equal() +
  xlab("Density of Wetlands") +
  ylab("Overall Index of Floodplain Integrity") +
  # geom_text(x= 0.9, y=0.1, label = paste0("R^2 = ",
round(R2.wetlands,2))) +
  theme_bw() +
  theme(text = element_text(size=16)) +
  labs(tag = "b)")
wetlands.plot

# Scatter plot of wetlands vs IFI by stream order
wetlands.plot.SO <- ggplot(na.omit(wetlands.comp), aes(x =
Area_Density, y = Overall)) +
  geom_point() +
  xlim(0,1) + ylim(0,1) +
  coord_equal() +
  xlab("Density of Wetlands") +
  ylab("Overall Index of Floodplain Integrity") +
  facet_wrap(~StrmOrder) +
  # geom_text(x= 0.9, y=0.1, label = paste0("R^2 = ",
round(R2.wetlands,2))) +
  theme_bw() +
  theme(text = element_text(size=14))
wetlands.plot.SO

grid.arrange(ICI.intersect.plot, wetlands.plot, ncol = 2)

################################
# Sensitivity analysis of Function IFI results

# Numeric value (1 to 5) to represent function with min value
func.sensitivity <- data.frame(HUC12 = as.character(all.data$HUC12))
func.sensitivity$min.func <- apply(func.IFI, 1, which.min)

# add function names
func.lookup <- data.frame(num = seq(1,5), names = c("Floods",
"Groundwater", "Sediment",

"Organics/Solutes", "Habitat"))
func.sensitivity$min.func.name <-
func.lookup$names[match(unlist(func.sensitivity$min.func),
func.lookup$num)]

# Standard deviation of function IFI
func.sensitivity$std.dev <- apply(func.IFI, 1, sd)

# Modified coefficient of variation (sd of functions / overall IFI
(geomean))
func.sensitivity$CV <- func.sensitivity$std.dev/all.data$IFI_geomean

# Plots to visualize sesitivity
func.plot <- ggplot(func.sensitivity, aes(min.func.name)) +
```

```
  geom_bar() +
  xlab("Function with Minimum IFI") +
  ylab("Number of Floodplain Units") +
  theme_bw() +
  theme(text = element_text(size=14))
func.plot

sd.hist <- ggplot(func.sensitivity, aes(x = std.dev)) +
  geom_histogram(binwidth = 0.02) +
  xlab("Standard deviation of Function IFI") +
  ylab("Number of Floodplain Units") +
  theme_bw() +
  theme(text = element_text(size=14))

sd.hist

# Investigate by stream order
func.sensitivity$StrmOrder <- all.data$StrmOrder

# plot Std dev and C.V. of function IFI by stream order
sd.SO <- ggplot(func.sensitivity, aes(StrmOrder, std.dev, group =
StrmOrder)) +
  geom_boxplot(na.rm = TRUE) +
  scale_x_discrete(name = "Stream Order", breaks = seq(1:8)) +
  ylab("Standard Deviation of Function IFI\n") +
  theme_linedraw() +
  theme(text = element_text(size=14), panel.grid.major.x =
element_blank(), panel.grid.major.y = element_blank(),
        panel.grid.minor.y = element_blank()) +
  geom_text(data = count.data, aes(StrmOrder, y =
max(func.sensitivity$std.dev), label = Freq),
            nudge_y = 0.05, size = 5)
sd.SO

cv.SO <- ggplot(func.sensitivity, aes(StrmOrder, CV, group =
StrmOrder)) +
  geom_boxplot(na.rm = TRUE) +
  scale_x_discrete(name = "Stream Order", breaks = seq(1:8)) +
  ylab("Coefficient of Variation of Function IFI\n") +
  theme_linedraw() +
  theme(text = element_text(size=20), panel.grid.major.x =
element_blank(), panel.grid.major.y = element_blank(),
        panel.grid.minor.y = element_blank()) +
  geom_text(data = count.data, aes(StrmOrder, y = 2.02, label = Freq),
size = 5)
cv.SO

# Plot minimum function by stream order
min.func.SO <- func.sensitivity %>%
  count(min.func.name, StrmOrder) %>%
  group_by(StrmOrder) %>%
  mutate(percent = n/sum(n))
```

```
# plot by percent
min.func.plot <- ggplot(min.func.SO, aes(x= StrmOrder, y = percent,
fill = min.func.name)) +
  geom_col(position = "fill") +
  scale_y_continuous(labels = percent) +
  scale_fill_manual(values = wes_palette(n=5, name = "Darjeeling1")) +
  xlab("Stream Order") +
  theme(text = element_text(size=14)) +
  labs(fill = "Minimum Function")
min.func.plot

min.func.plot2 <- ggplot(min.func.SO, aes(x= StrmOrder, y = n, fill =
min.func.name)) +
  geom_col() +
  scale_y_continuous(name = "Count of Floodplain Units") +
  scale_fill_manual(values = wes_palette(n=5, name = "Darjeeling1")) +
  xlab("Stream Order") +
  theme(text = element_text(size=14)) +
  labs(fill = "Minimum Function")
min.func.plot2

# output sensitivity result as csv
write.csv(func.sensitivity, file = paste(out.path,
"/IFI_sensitivity.csv", sep=""))

############################
# IFI function to overall ratio

func.ratio <- apply(func.IFI, 2, function(x) x/all.data$IFI_geomean)

# Plot boxplots
ratio.df <- melt(func.ratio)
levels(ratio.df$Var2) = c("Flood Reduction", "Groundwater Storage",
"Sediment Regulation",
                             "Organics/Solutes Regulation", "Habitat
Provision")

ratio.plot <- ggplot(ratio.df, aes(x = Var2, y = value)) +
  geom_boxplot() +
  geom_hline(yintercept = 1, linetype = "dashed", size = 1) +
  scale_x_discrete(labels = function(x) str_wrap(x, width = 10)) +
  labs( y = "Ratio of Function to Overall IFI\n", x = NULL) +
  theme_linedraw() +
  theme(text = element_text(size=16), panel.grid.major.x =
element_blank(), panel.grid.major.y = element_blank(),
        panel.grid.minor.y = element_blank(), legend.position =
"none")
ratio.plot

# Test for significant differences
```

```
# clean INF and remove
ratio.df <- ratio.df[!is.infinite(ratio.df$value),]
ratio.lm <- lm(value ~ Var2, data = ratio.df)
ratio.pairwise <- lsmeans(ratio.lm, pairwise ~ Var2)
method.contrasts <- ratio.pairwise$contrasts
method.contrasts
# results: all significantly different except sediment and organics
```

6. IFI results mapping

This R script, ResultsMapping.R, makes spatial plots of the results of the IFI computation. These maps are mostly included as figures in this report.

Code:

```
################
# Floodplain Integrity Assessment
# Mapping of floodplain integrity results
# M. Karpack, Spring 2019

# Plots the results of the IFI analysis
# including figures for publication

library(ggplot2)
library(RColorBrewer)
library(wesanderson)
library(rgeos)
library(rgdal)
library(dplyr)
library(tidyr)
library(broom)
library(gridExtra)
library(reshape2)
library(ggmap)

# Set working directory
setwd("C:/Users/mnk5/Documents/floodplain_integrity")

# read in files
floodplain <- readOGR(dsn = "RawData/SpatialData", layer =
"CO_FP_IFI")
CO.boundary <- readOGR(dsn = "RawData/SpatialData", layer =
"CO_StateBoundary_UTM")
CO.HUC12 <- readOGR(dsn = "RawData/SpatialData", layer =
"CO_HUC12_IFI")
# NHD v1 segments order 4 and larger in Colorado
CO.rivers <- readOGR(dsn = "RawData/SpatialData", layer =
"NHDv1_Order4_CO")

# Clean data
floodplain$HUC12 <- as.character(floodplain$HUC12)
CO.HUC12$HUC12 <- as.character(CO.HUC12$HUC12)

# transform for ggplot
floodplain_tidy <- tidy(floodplain, region = "HUC12")
floodplain.df <- left_join(floodplain_tidy, floodplain@data, by =
c("id" = "HUC12"))
```

```
HUC12_tidy <- tidy(CO.HUC12, region = "HUC12")
HUC12.df <- left_join(HUC12_tidy, CO.HUC12@data, by = c("id" =
"HUC12"))

CO.boundary@data$id <- row.names(CO.boundary@data)
CO.boundary_tidy <- tidy(CO.boundary, region = 'id')

CO.rivers@data$id <- row.names(CO.rivers@data)
CO.rivers_tidy <- tidy(CO.rivers, region = 'id')

###############################
# Plot results

# choose bounding box area for zoomed in area
zoomsize <- 50000
xlimits <- c(494000,494000 + zoomsize)
ylimits <- c(4506000, 4506000 - zoomsize)

# Floodplains in state
map <- ggplot(data = floodplain.df, aes(x = long, y = lat, group =
group)) +
  geom_polygon(data = CO.boundary_tidy, aes(x = long, y = lat, group =
group), fill = "grey97") +
  geom_polygon(data = floodplain.df, aes(x = long, y = lat, group =
group), fill = "grey50") +
  geom_path(data = CO.rivers_tidy, aes(x = long, y = lat, group =
group), color = "mediumblue", size = 0.25) +
  geom_rect(aes(xmin = min(xlimits), xmax = max(xlimits), ymin =
min(ylimits), ymax = max(ylimits)),
            fill = "transparent", color = "red", size = 1.5) +
  coord_equal() +
  labs(x = NULL, y = NULL) +
  theme_minimal(base_size = 14) +
  theme(legend.text = element_text(size = 8)) +
  theme(axis.text=element_blank()) +
  theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())

map

# Overall IFI

map1 <- ggplot(data = floodplain.df, aes(x = long, y = lat, group =
group, fill = IFI_geomea)) +
  geom_polygon(data = CO.boundary_tidy, aes(x = long, y = lat, group =
group), fill = "grey93") +
  geom_polygon(data = floodplain.df, aes(x = long, y = lat, group =
group, fill = IFI_geomea)) +
  coord_equal() +
  # coord_fixed(ratio = 1, xlim = xlimits, ylim = ylimits) +
  scale_fill_gradientn(colours = c("chocolate3", "wheat1"
,"darkcyan"), breaks = seq(0, 1, by = 0.2))
```

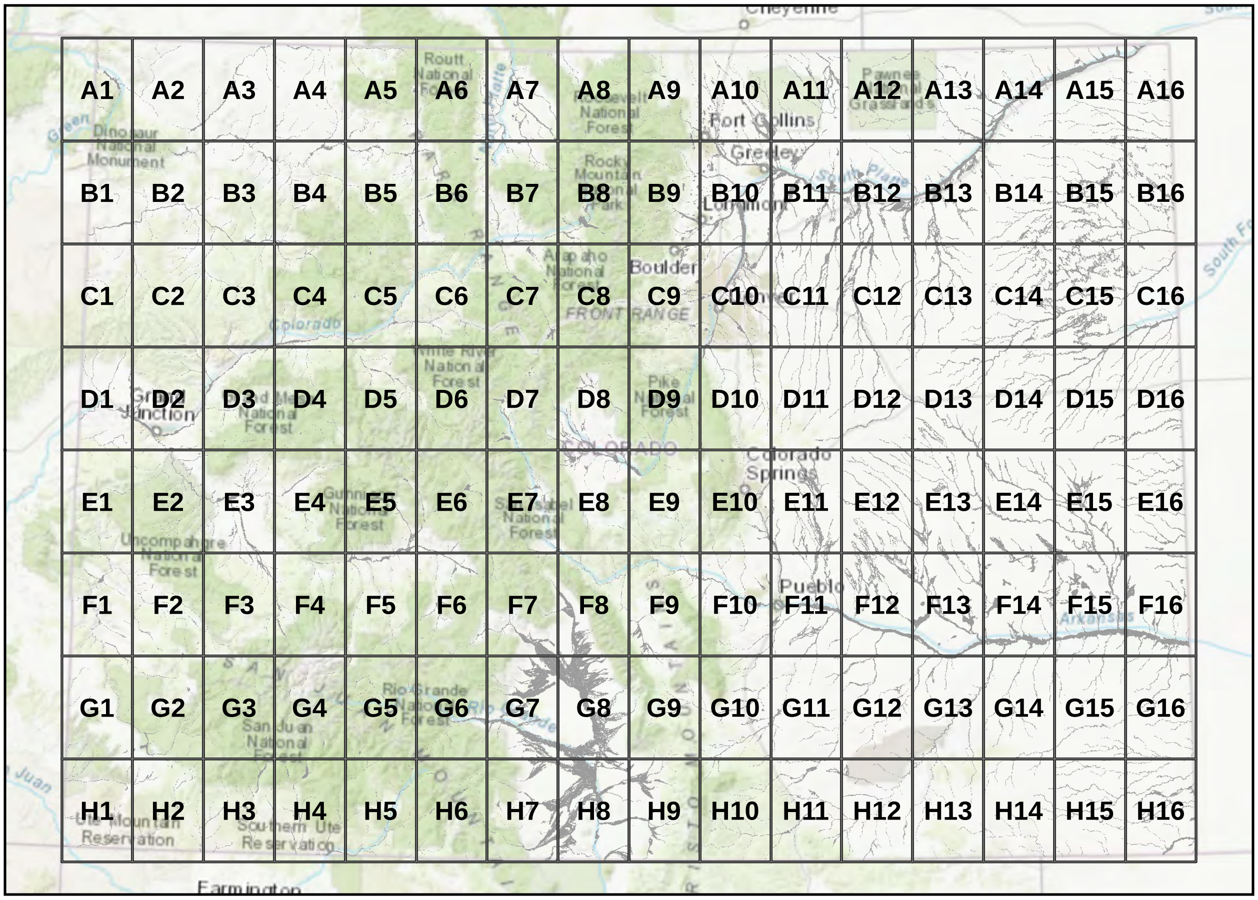
```
map1 <- map1 + labs(x = NULL, y = NULL, fill = "IFI")
map1 <- map1 + theme_minimal(base_size = 14) +
  theme(legend.text = element_text(size = 14)) +
  theme(axis.text=element_blank()) +
  theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())

map1

# Overall IFI mapped to HUC-12 units

map2 <- ggplot(data = HUC12.df, aes(x = long, y = lat, group = group))
+
  geom_polygon(data = HUC12.df, color = "grey27", size = 0.1, aes(x =
long, y = lat, group = group, fill = IFI_geomea)) +
  geom_polygon(data = CO.boundary_tidy, aes(x = long, y = lat, group =
group),
               fill = NA, color = "black", size = 1.5) +
  geom_path(data = CO.rivers_tidy, aes(x = long, y = lat, group =
group), color = "navy", size = 1) +
  coord_equal() +
  # coord_fixed(ratio = 1, xlim = xlimits, ylim = ylimits) +
  scale_fill_gradientn(colours = c("chocolate3", "wheat1"
,"darkcyan"), breaks = seq(0, 1.0, by = 0.2),
                       labels = c("0.0","0.2", "0.4", "0.6", "0.8",
"1.0"), limits = c(0,1)) +
  labs(x = NULL, y = NULL, fill = "IFI") +
  theme_minimal(base_size = 12) +
  theme(legend.text = element_text(size = 12)) +
  theme(axis.text=element_blank()) +
  theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())

map2


###################################
# Map minimum function to HUC-12

# put functions in order
HUC12.df$MinFunc <- factor(HUC12.df$MinFunc,
       levels = c("Floods", "Groundwater", "Sediment",
"Organics/Solutes", "Habitat"),
       ordered = TRUE)

min.map <- ggplot(data = HUC12.df, aes(x = long, y = lat, group =
group)) +
  geom_polygon(data = HUC12.df, color = "grey27", size = 0.1, aes(x =
long, y = lat, group = group, fill = MinFunc)) +
  geom_polygon(data = CO.boundary_tidy, aes(x = long, y = lat, group =
group),
               fill = NA, color = "black", size = 1.5) +
```

```
  geom_path(data = CO.rivers_tidy, aes(x = long, y = lat, group =
group), color = "navy", size = 1) +
  coord_equal() +
  scale_fill_manual(values = wes_palette(n=5, name = "Darjeeling1")) +
  # coord_fixed(ratio = 1, xlim = xlimits, ylim = ylimits) +
  labs(x = NULL, y = NULL, fill = "Minimum Function") +
  theme_minimal(base_size = 12) +
  theme(legend.text = element_text(size = 12)) +
  theme(axis.text=element_blank()) +
  theme(panel.grid.major = element_blank(), panel.grid.minor =
element_blank())

min.map

###################################
# # All IFI by function

# Mapping zoomed in area IFI by function
fp.df <- melt(floodplain.df, id = 1:9, measure = 13:18)
levels(fp.df$variable) = c("Flood Reduction", "Groundwater Storage",
"Sediment Regulation",
                           "Organics/Solutes Regulation", "Habitat
Provision", "Overall IFI")



map7 <- ggplot(data = fp.df, aes(x = long, y = lat, group = group,
fill = value)) +
  # geom_polygon(data = CO.boundary_tidy, aes(x = long, y = lat, group
= group), fill = "grey93") +
  geom_polygon() +
  # coord_equal() +
  coord_fixed(ratio = 1, xlim = xlimits, ylim = ylimits) +
  facet_wrap(~ variable, ncol = 3) +
  scale_fill_gradientn(colours = c("chocolate3", "wheat1"
,"darkcyan"), breaks = seq(0, 1, by = 0.2)) +
  labs(x = NULL, y = NULL, fill = "IFI") +
  theme_minimal(base_size = 16) +
  theme(panel.background = element_rect(fill = "grey93"),
        panel.border = element_rect(fill = NA, colour = "black"),
        legend.position = "bottom",
        legend.text = element_text(size = 12),
        legend.key.width = unit(1, "cm"),
        axis.text=element_blank(),
        panel.grid.major = element_blank(), panel.grid.minor =
element_blank())
map7
```

Appendix C: Map of overall IFI for Colorado

This appendix contains a tiled map of overall floodplain integrity for the entire state of Colorado.

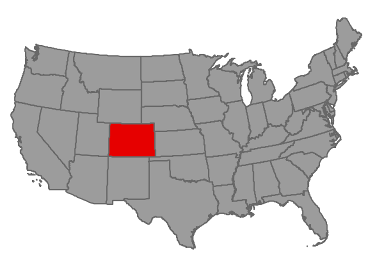
Overall IFI Map Index

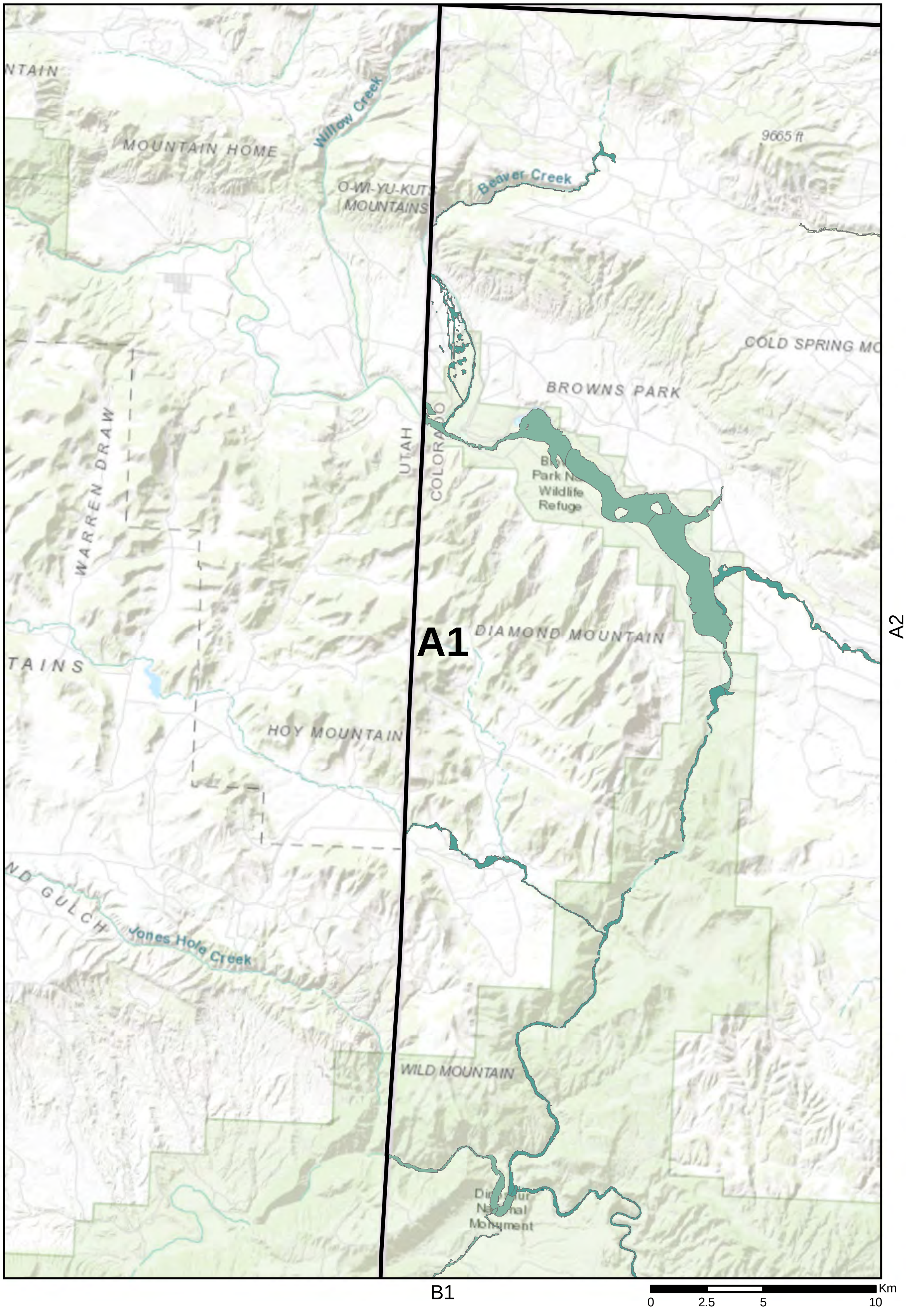


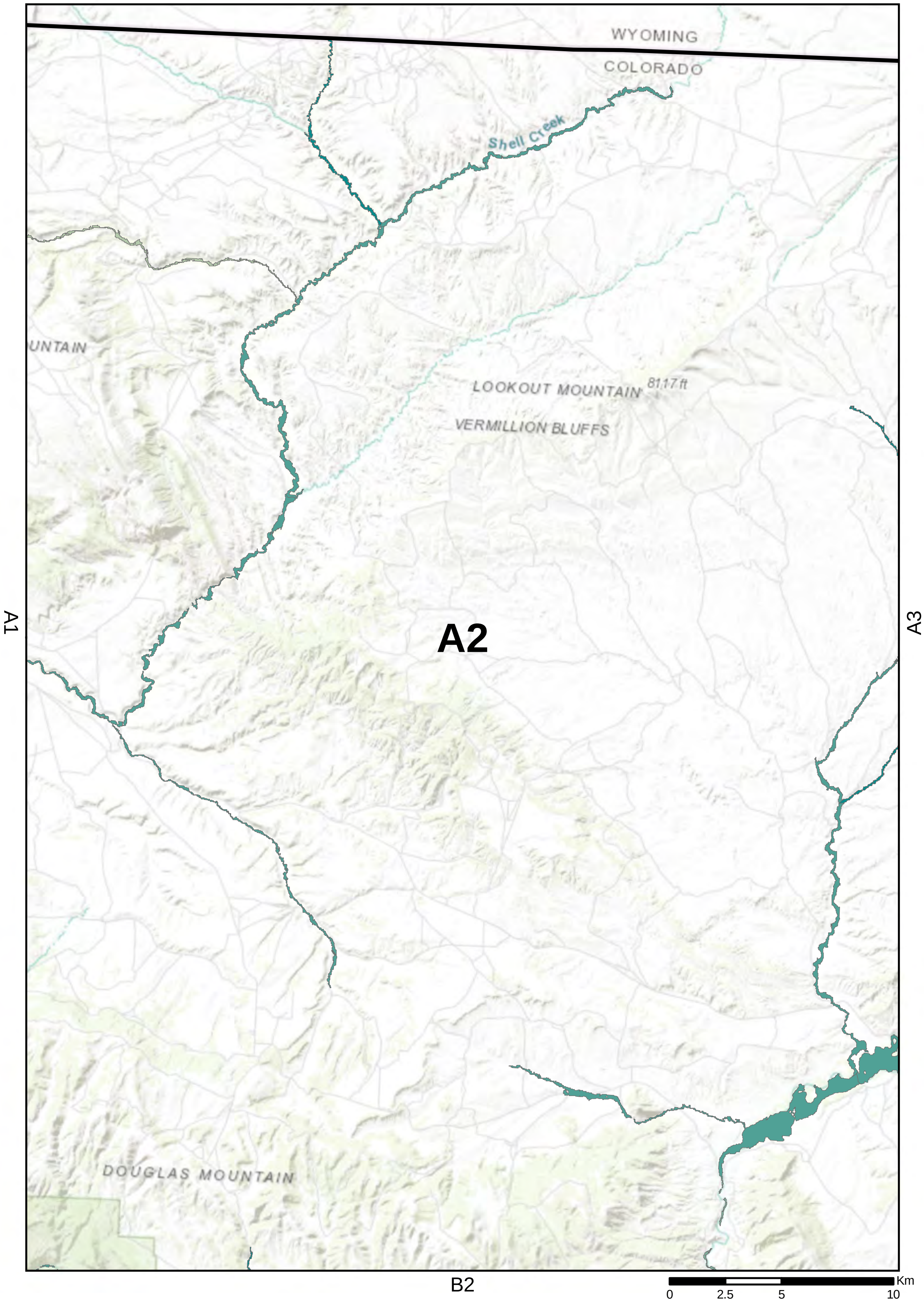
Service Layer Credits: Sources: Esri, HERE, Garmin, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, © OpenStreetMap contributors, and the GIS User Community

Overall IFI Value

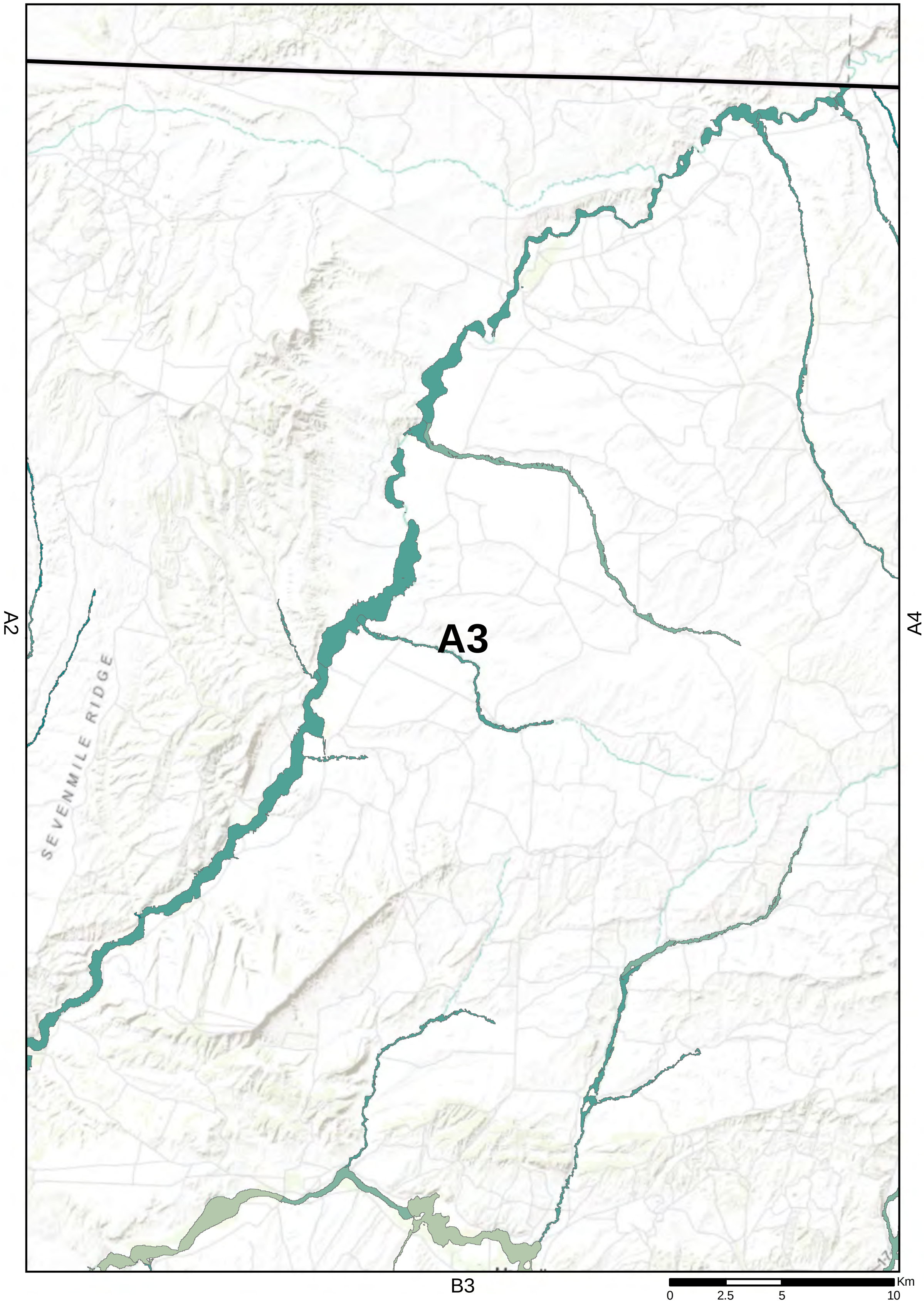
0.0 - 0.1	0.5 - 0.6
0.1 - 0.2	0.6 - 0.7
0.2 - 0.3	0.7 - 0.8
0.3 - 0.4	0.8 - 0.9
0.4 - 0.5	0.9 - 1.0

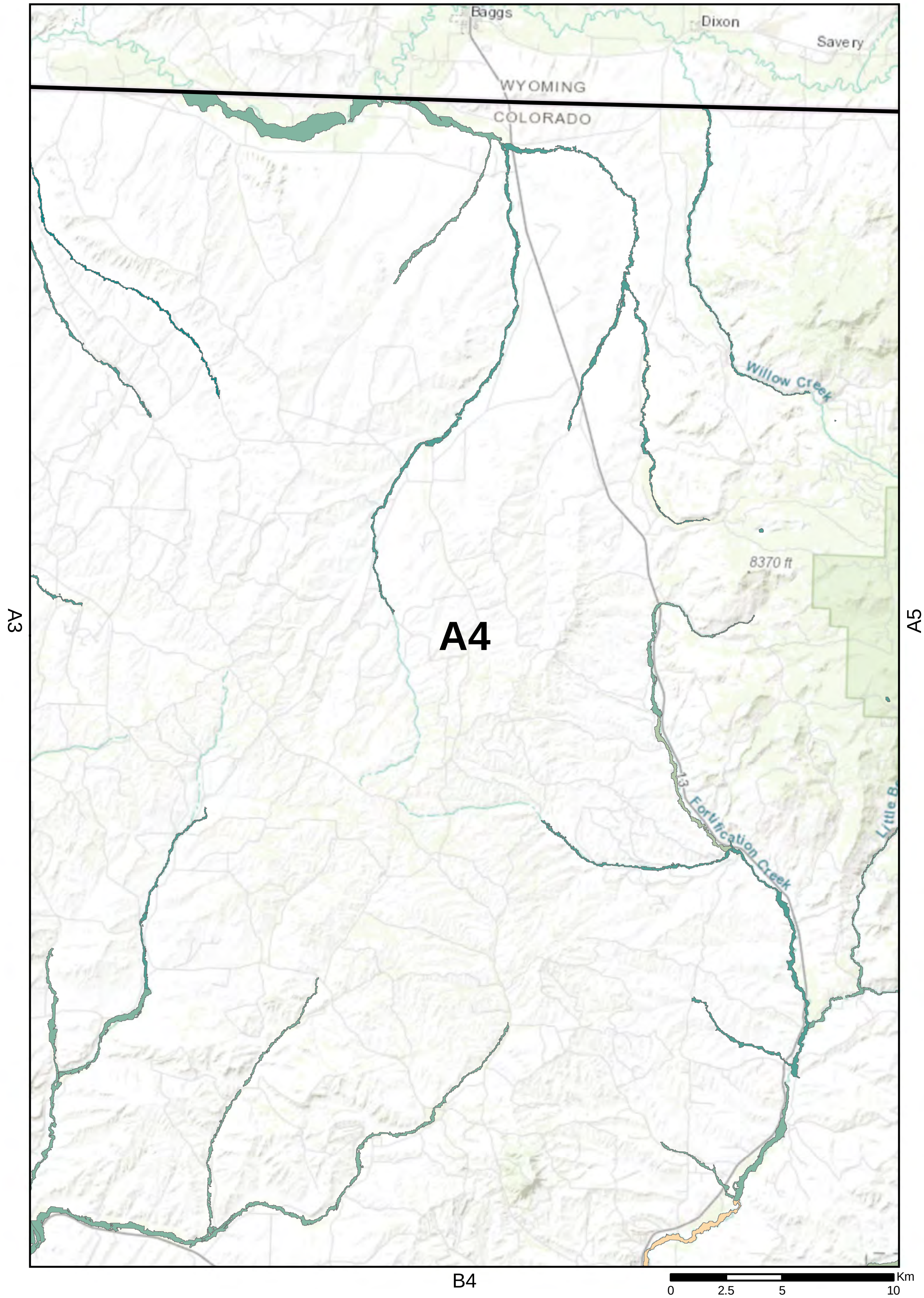


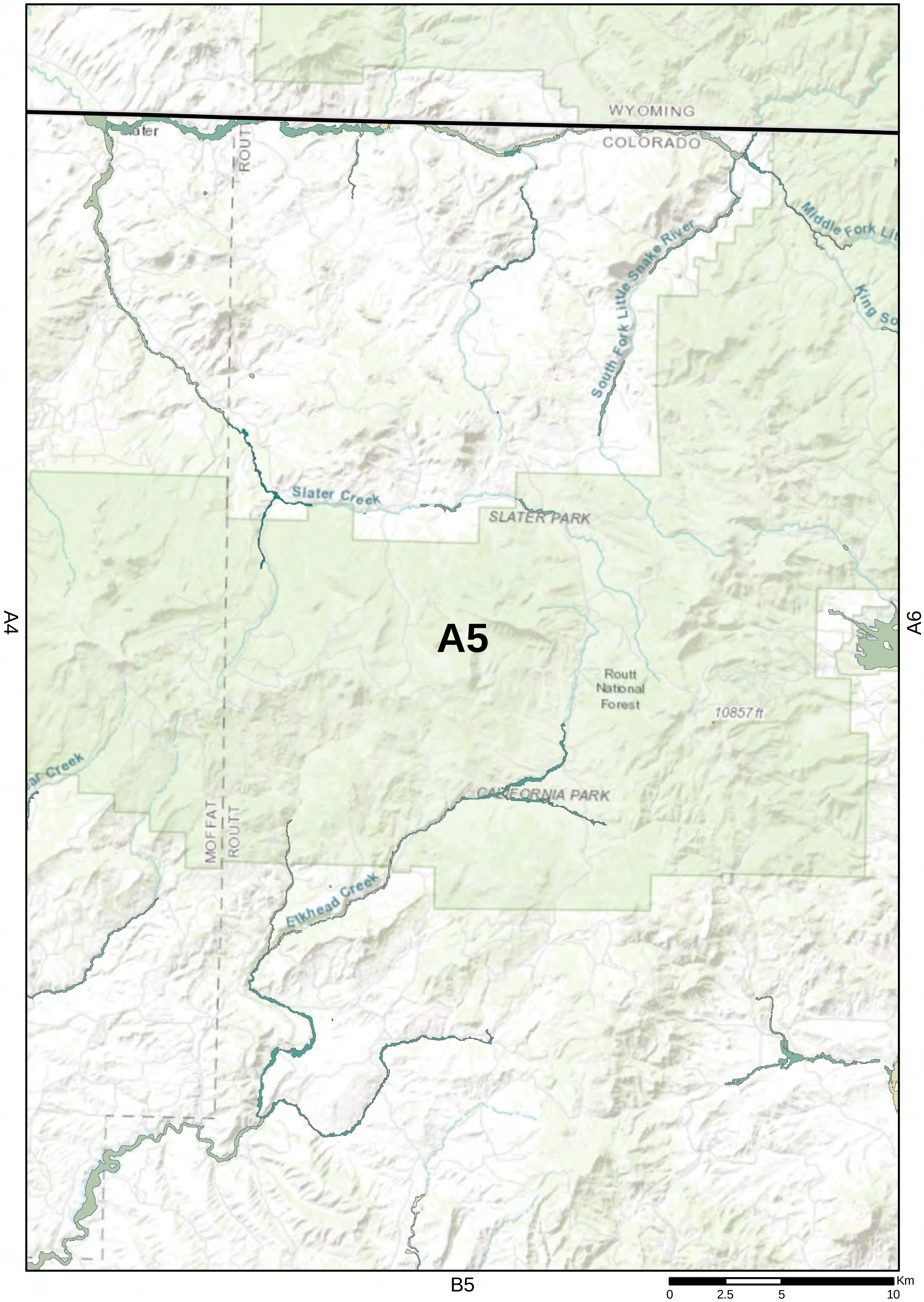

MOUNTAIN HOME
Willow Creek
O-WI-YU-KUT
MOUNTAINS
Beaver Creek
9665 ft
COLD SPRING MO
BROWNS PARK
UTAH
COLORADO
Wildlife
Refuge
WARREN DRAW
TAINS
A1
DIAMOND MOUNTAIN
HOY MOUNTAIN
Jones Hole Creek
WILD MOUNTAIN
A2
B1
Km
0
2.5
5
10

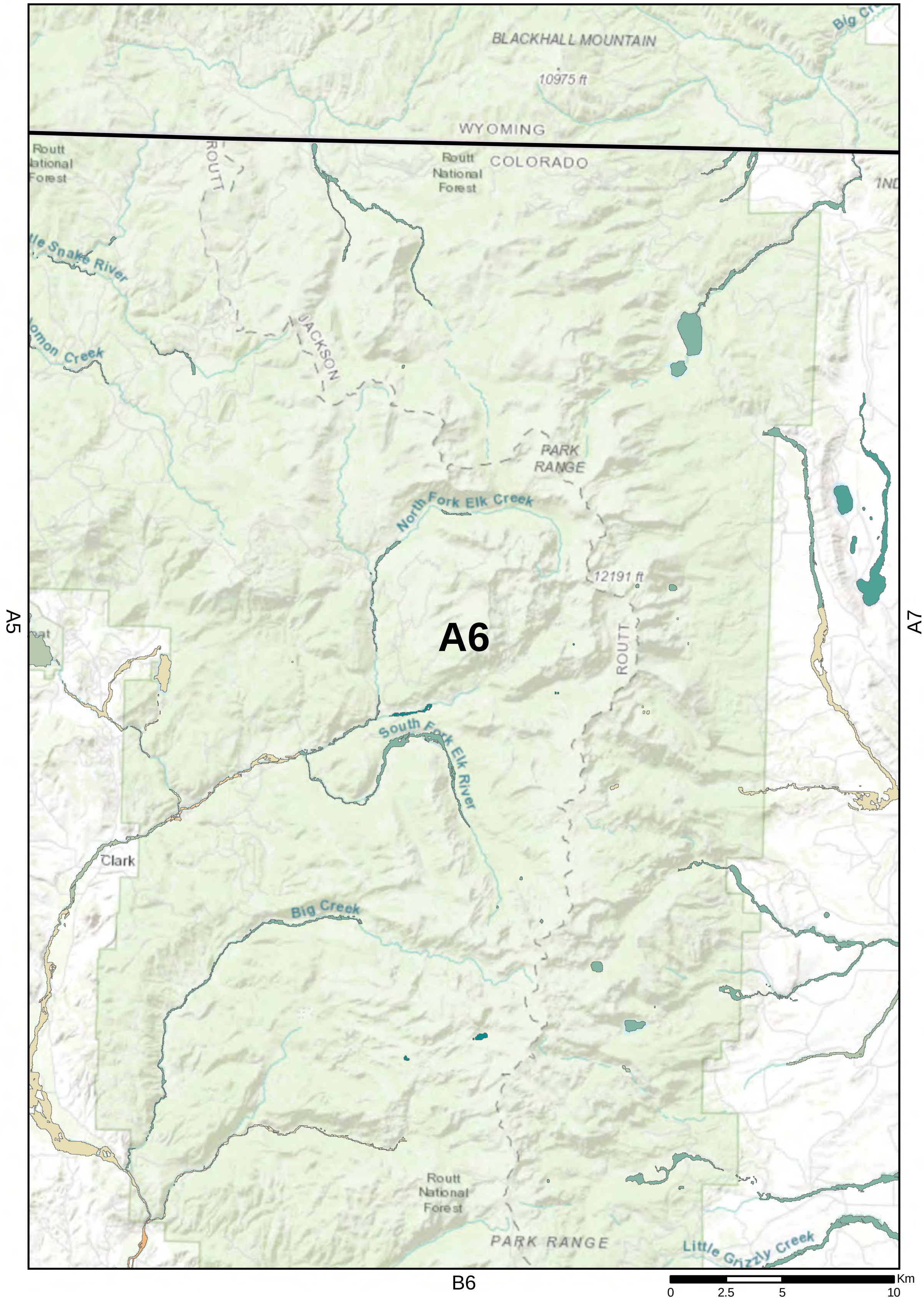


WYOMING
COLORADO
Shell Creek
UNTAIN
LOOKOUT MOUNTAIN
8117 ft
VERMILLION BLUFFS
A2
A1
A3
DOUGLAS MOUNTAIN
B2
Km
0
2.5
5
10

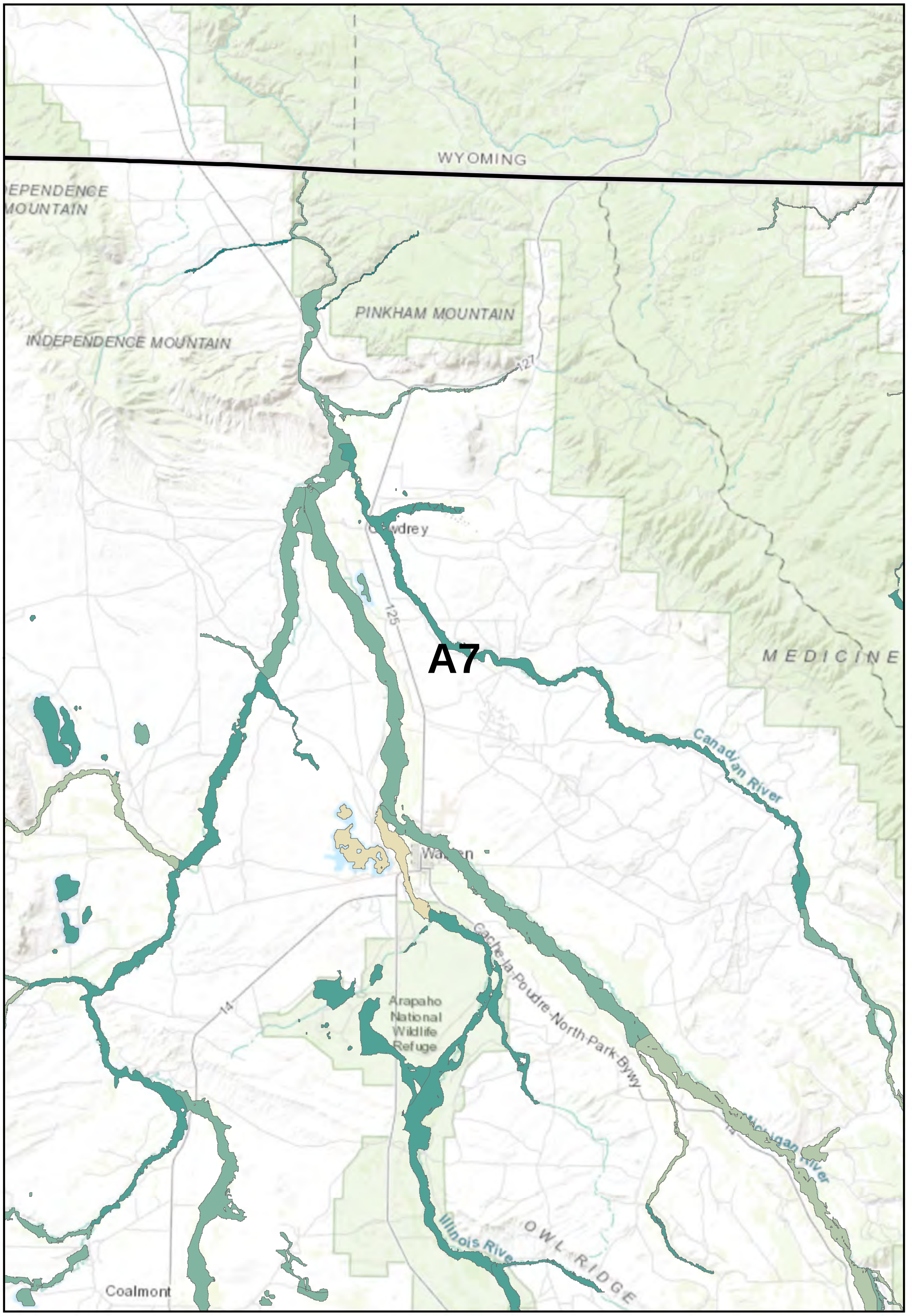

A3
A2
A4
B3
SEVENMILE RIDGE
Km
0
2.5
5
10


Baggs
Dixon
Savery
WYOMING
COLORADO
Willow Creek
8370 ft
A4
13
Fortification Creek
A3
A5
B4
Km
0
2.5
5
10


WYOMING
COLORADO
ROUTT
Middle Fork
King
South Fork Little Snake River
Slater Creek
SLATER PARK
A5
Routt National Forest
10857 ft
Creek
CALIFORNIA PARK
MOFFAT
ROUTT
Elkhead Creek
A4
A6
B5
Km
0
2.5
5
10



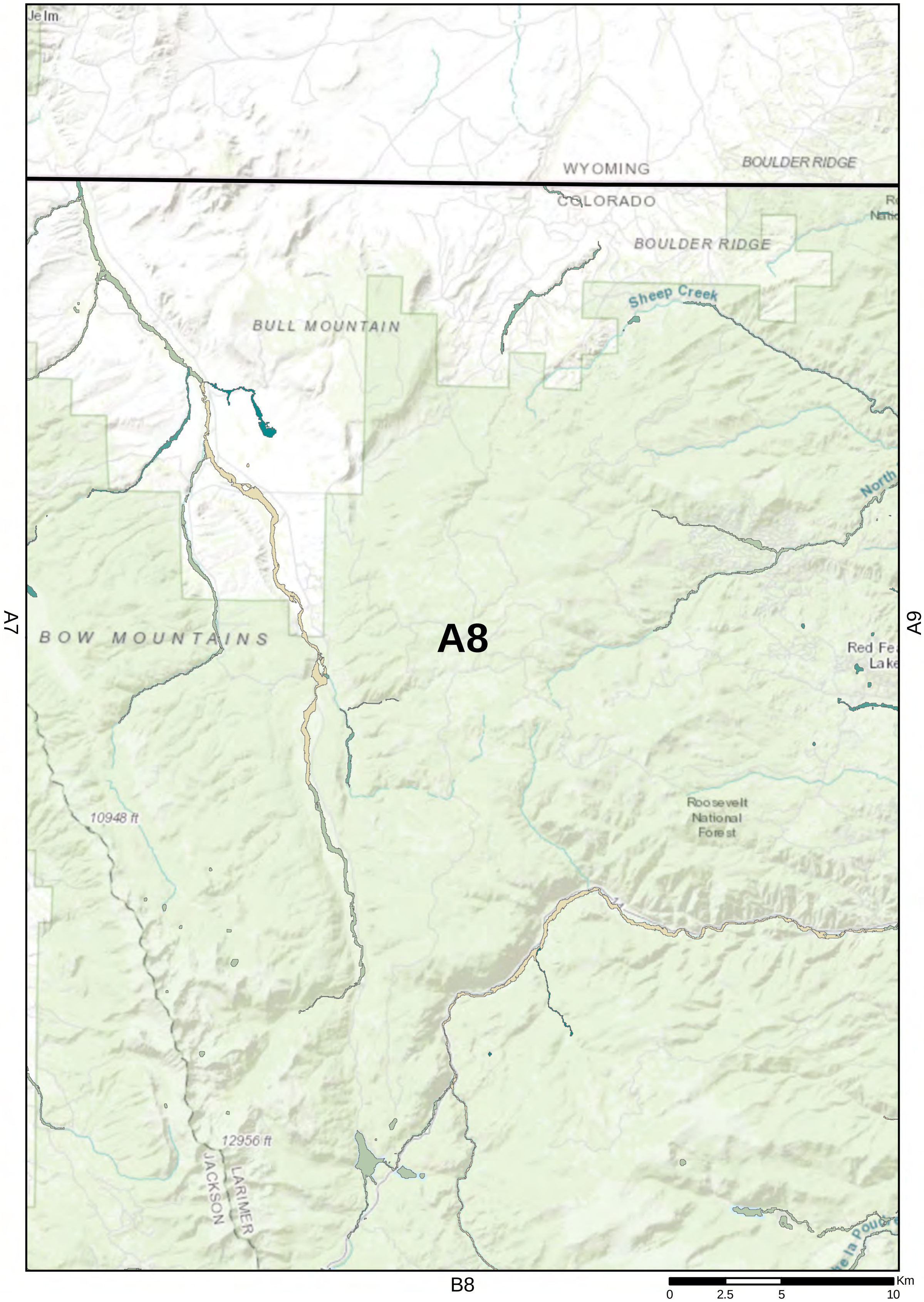
BLACKHALL MOUNTAIN
10975 ft
WYOMING
COLORADO
Routt National Forest
ROUTT
JACKSON
PARK RANGE
North Fork Elk Creek
12191 ft
A6
South Fork Elk River
Clark
Big Creek
PARK RANGE
Little Grizzly Creek
A5
A7
B6
0 2.5 5 10 Km

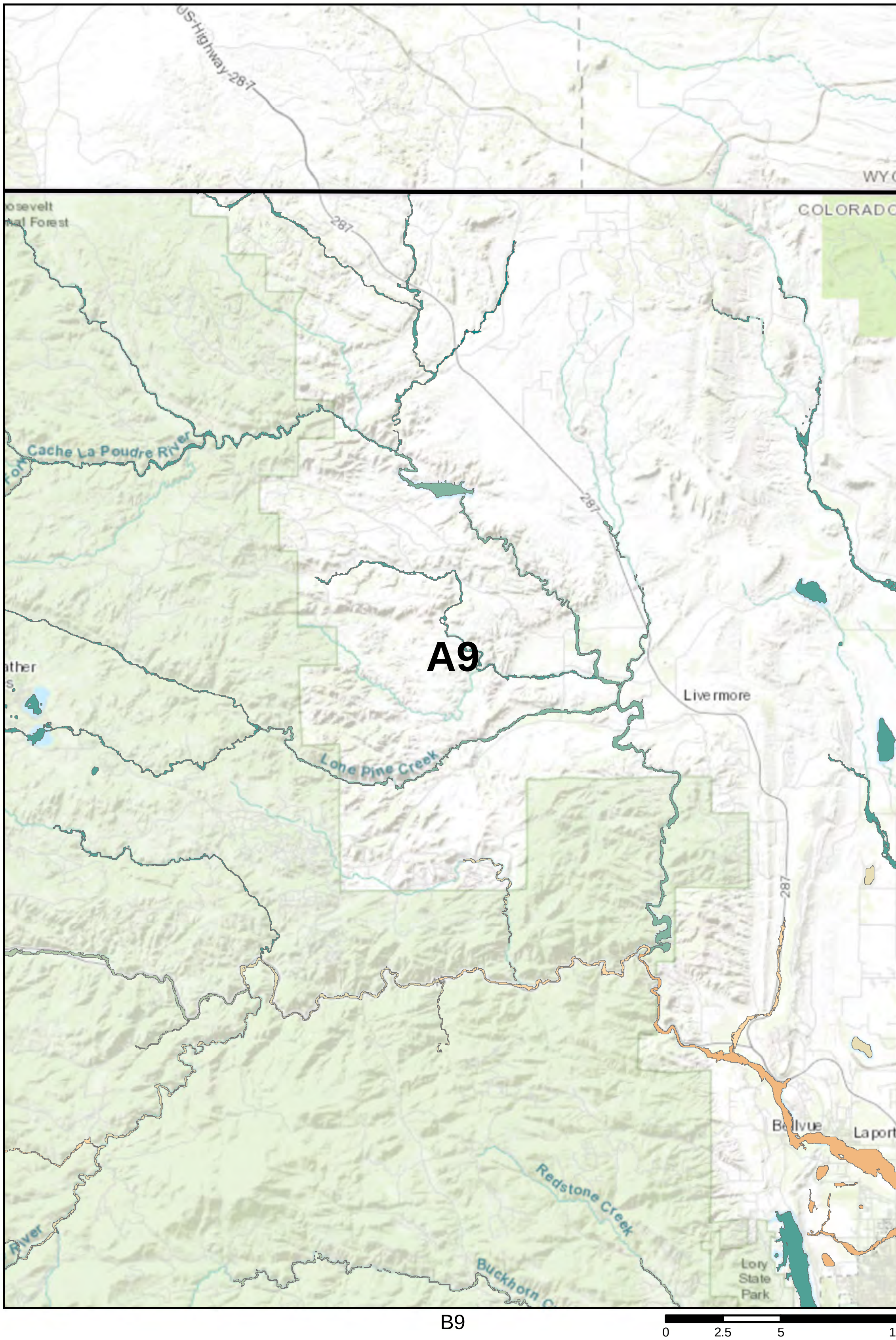

WYOMING
EPENDENCE
MOUNTAIN
PINKHAM MOUNTAIN
INDEPENDENCE MOUNTAIN
127
Cowdrey
125
A7
MEDICINE
Canadian River
Walden
Cache la Poudre-North Park Bywy
14
Arapaho
National
Wildlife
Refuge
Michigan River
Illinois River
OWL RIDGE
Coalmont
Km
0
2.5
5
10

A6

A8

B7

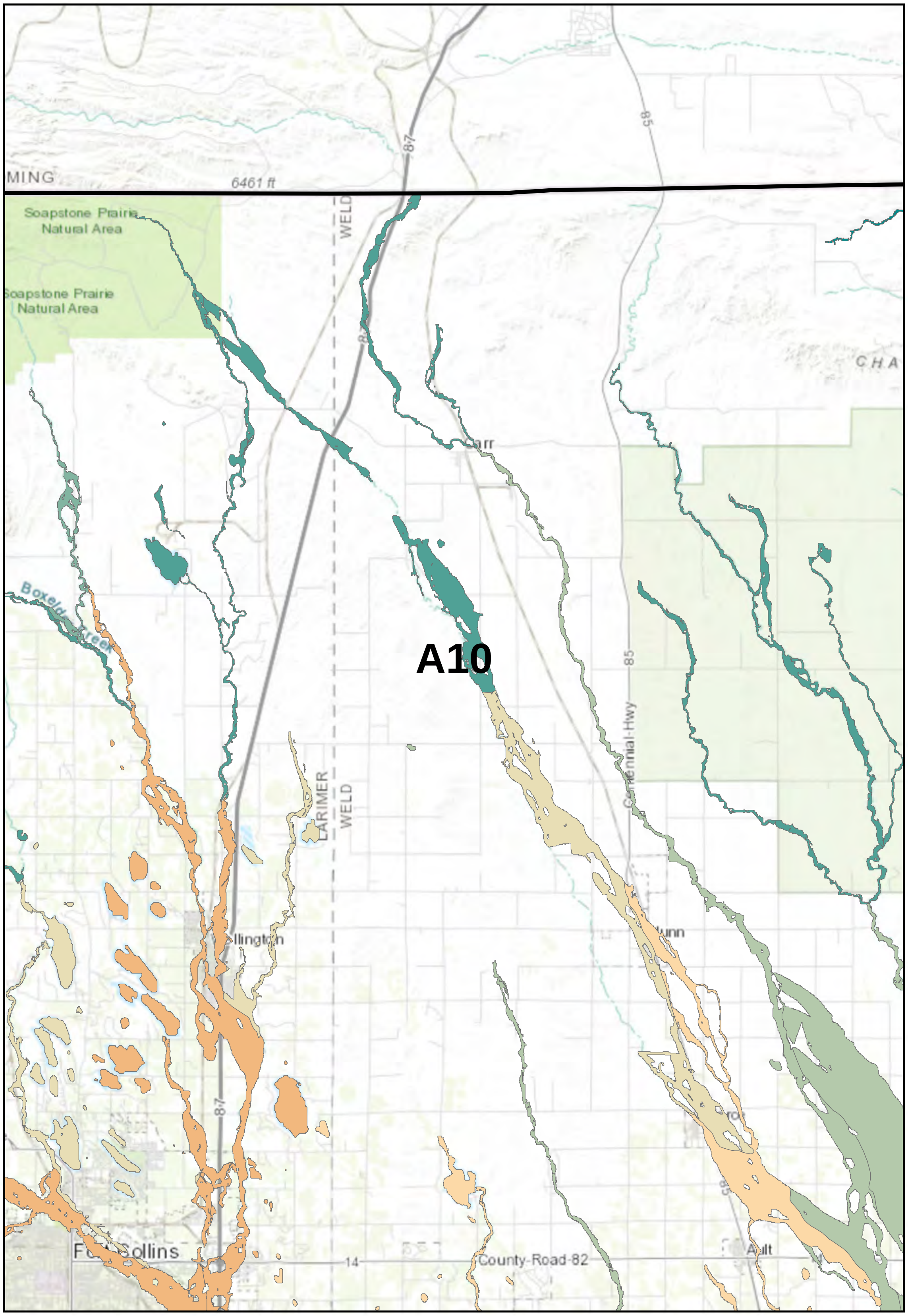

A7
A8
A9
B8
Jelm
WYOMING
BOULDER RIDGE
COLORADO
BOULDER RIDGE
Sheep Creek
BULL MOUNTAIN
BOW MOUNTAINS
Red Fe
Lake
Roosevelt
National
Forest
10948 ft
12956 ft
JACKSON
LARIMER
Km
0
2.5
5
10


US-Highway-287
287
WY
COLORADO
osevelt
nal Forest
Cache La Poudre River
A9
Livermore
Lone Pine Creek
Bellvue
Laporte
Redstone Creek
Buckhorn C
Lory
State
Park
River
Km
0
2.5
5
10

A8

A10

B9



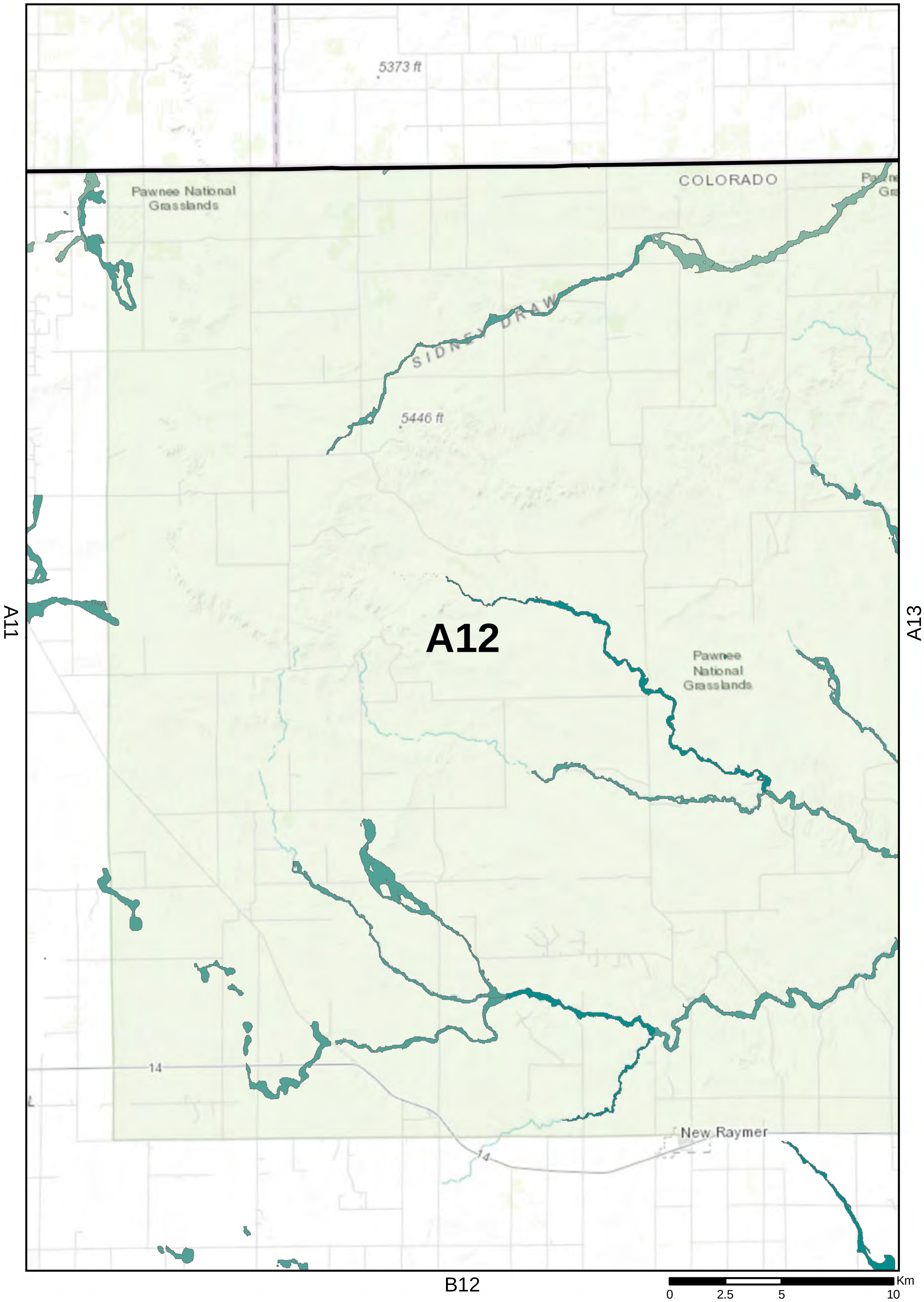
A9

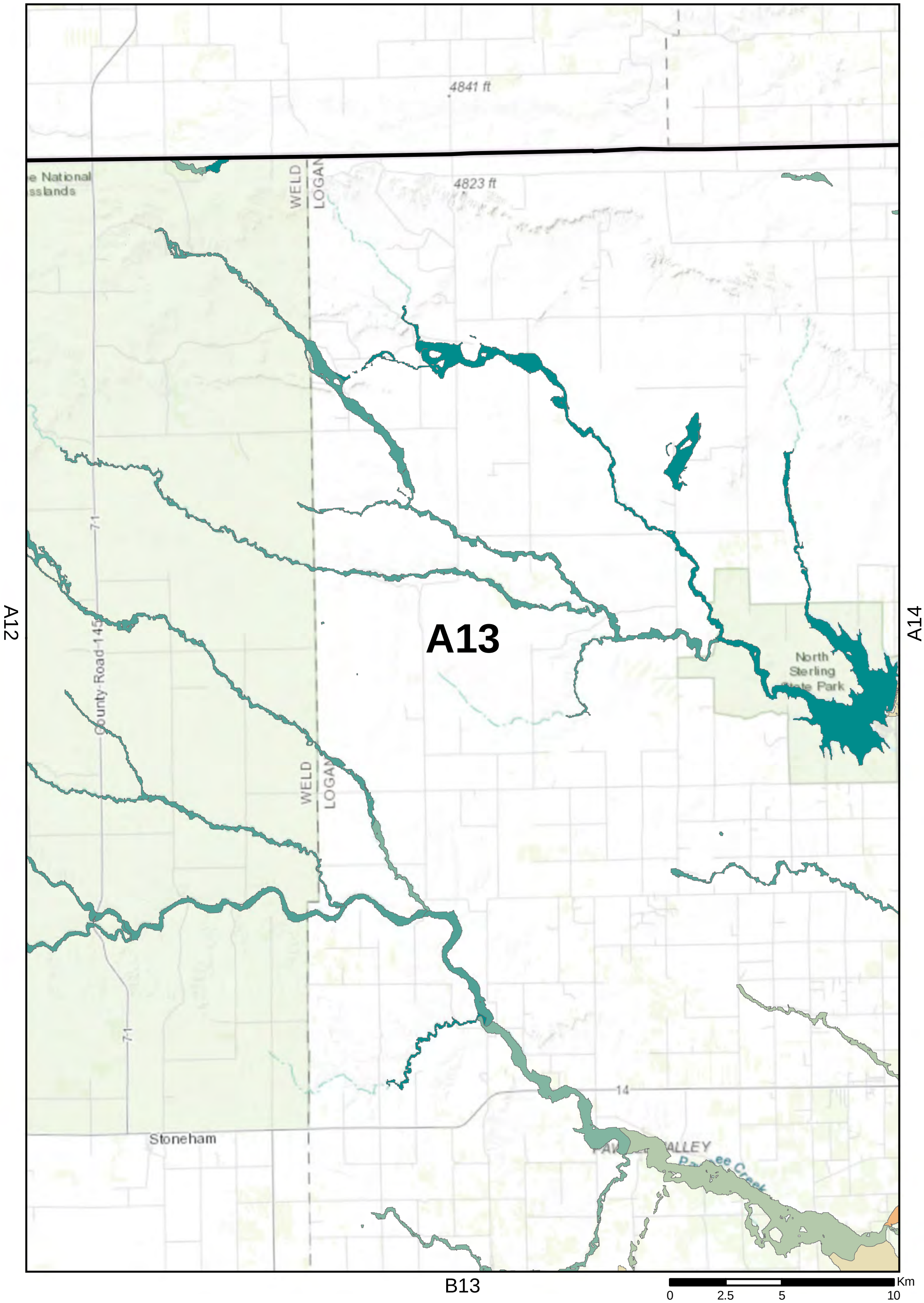
A11

B10

0 2.5 5 10 Km

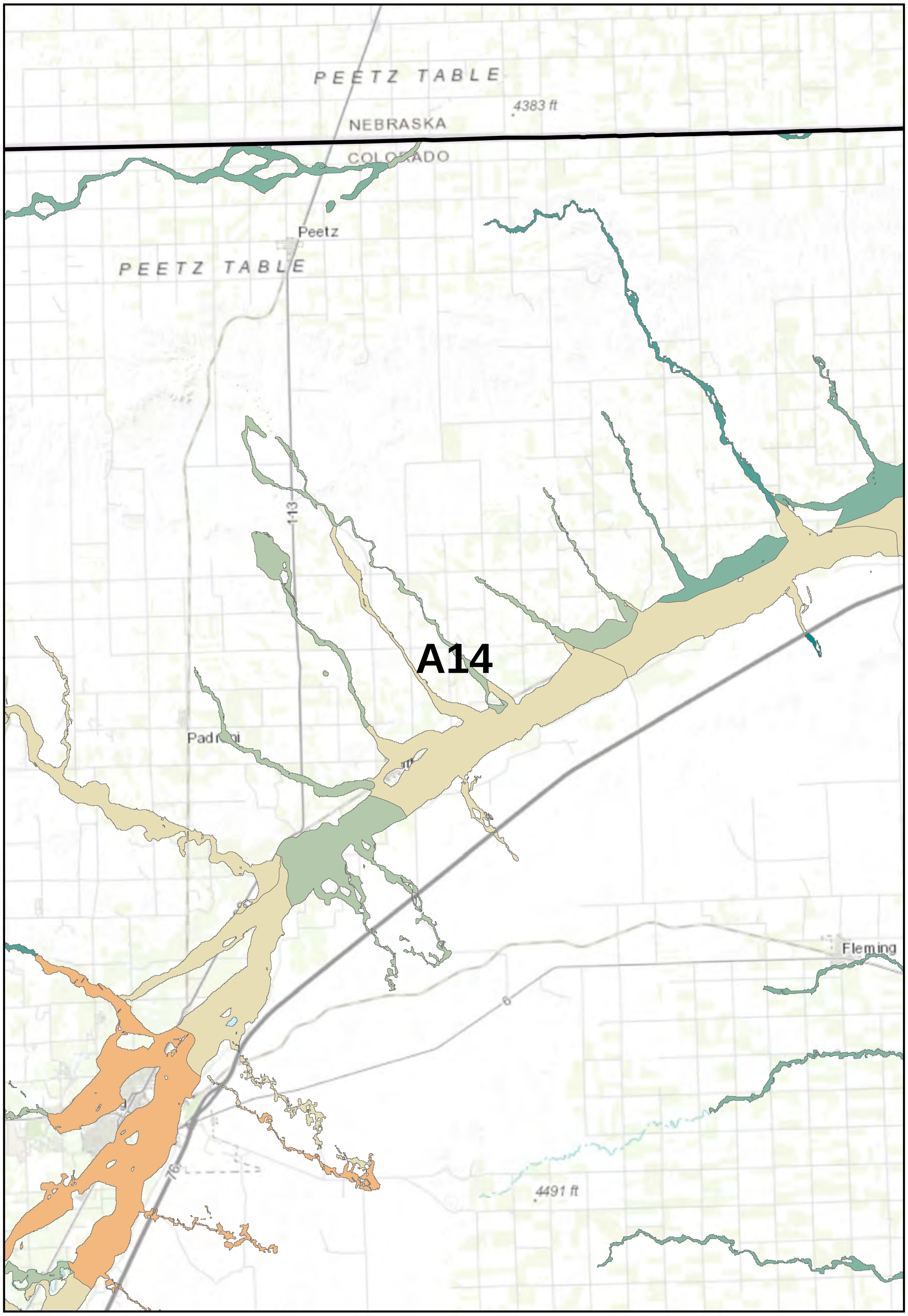

Carpenter
WYOMING
COLORADO
5607 ft
Hereford
A11
Pawnee National Grasslands
14
Briggsdale
SEVEN CROSS HIL
A10
A12
B11
Km
0
2.5
5
10


5373 ft
COLORADO
Pawnee National Grasslands
SIDNEY DRAW
5446 ft
A12
Pawnee National Grasslands
A11
A13
14
New Raymer
B12
Km
0
2.5
5
10



A13
A12
A14
B13
4841 ft
4823 ft
WELD
LOGAN
North Sterling State Park
County Road 145
Stoneham
14
0
2.5
5
10
Km

A13

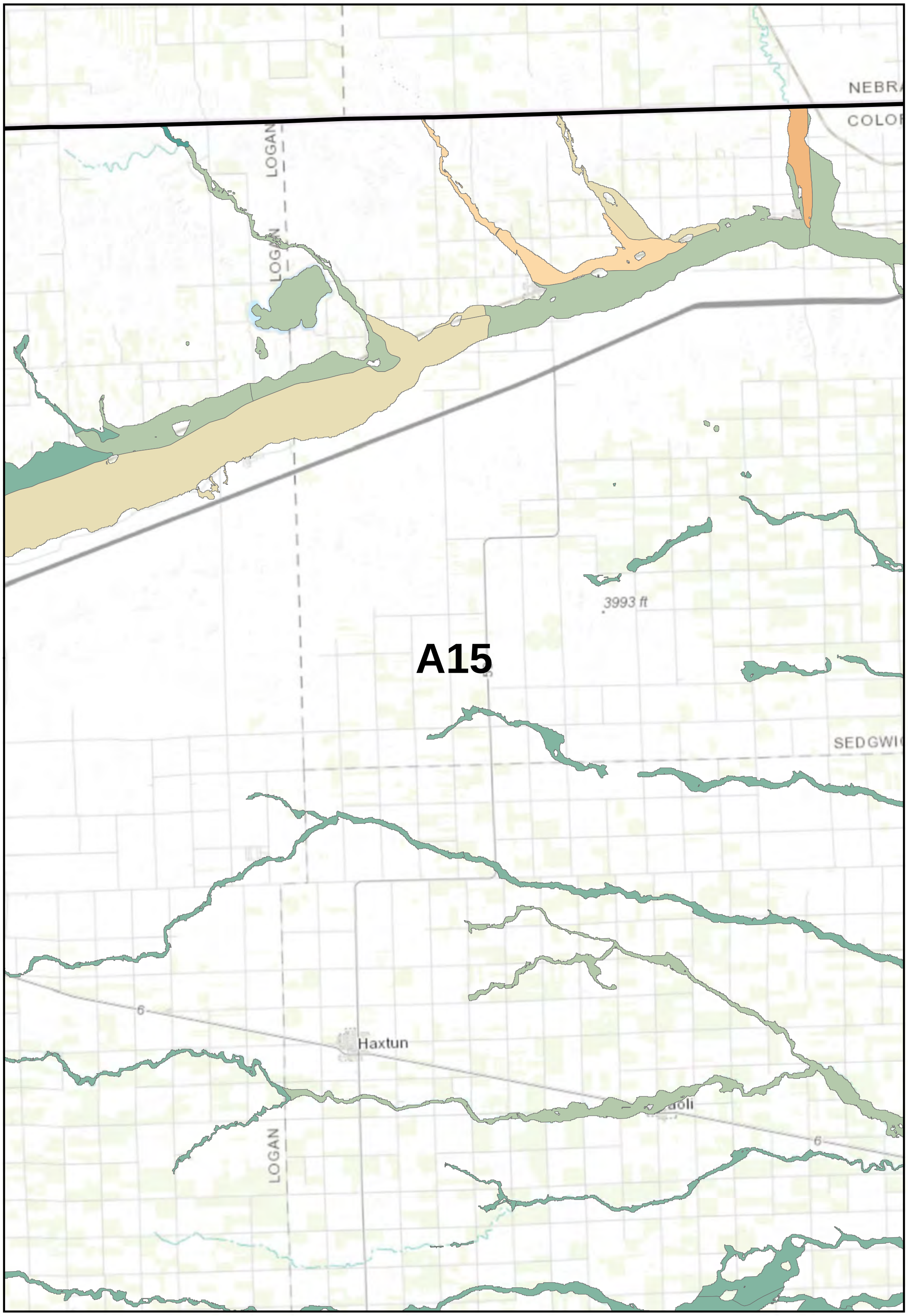


A15

B14

0 2.5 5 10 Km

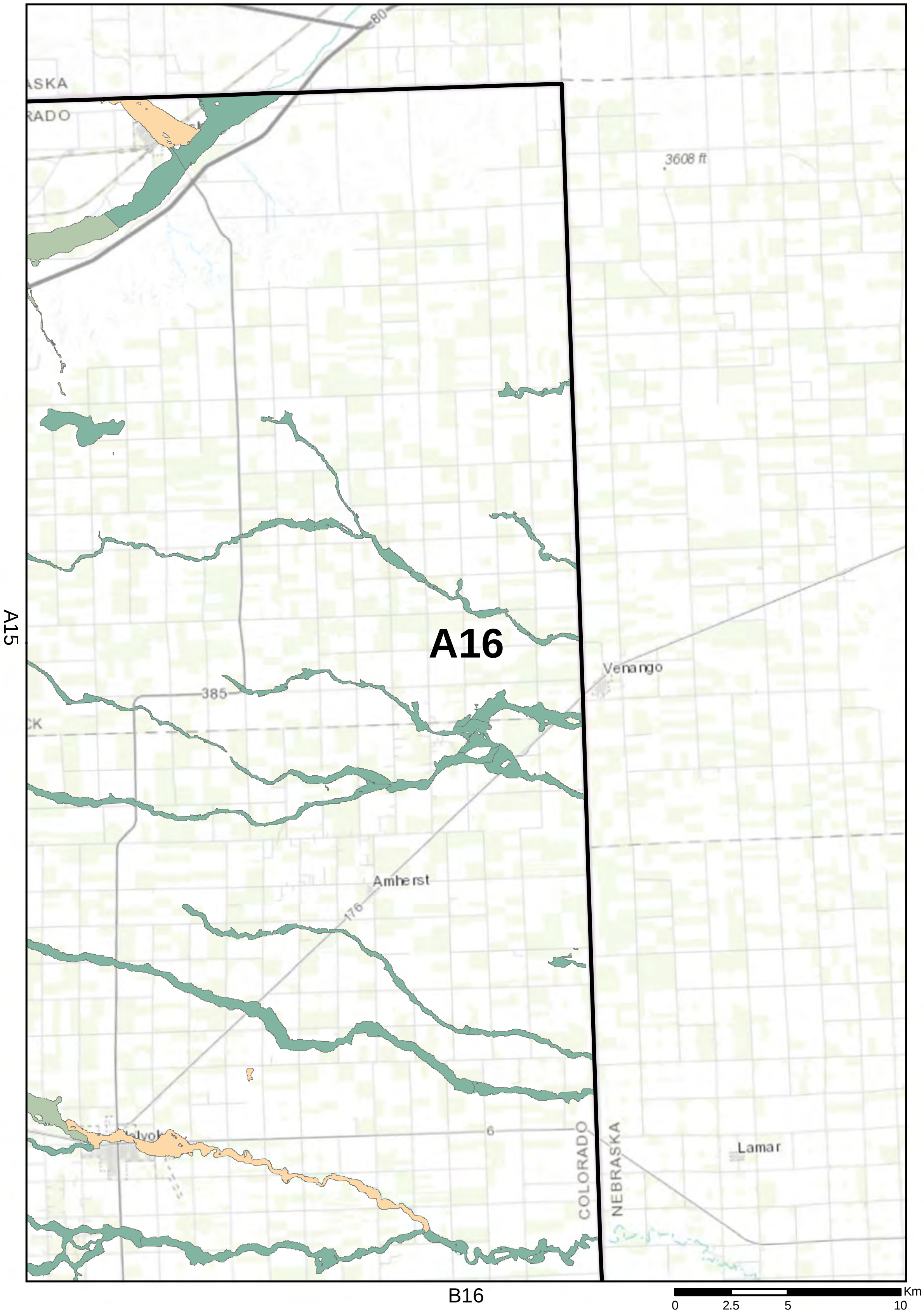
A14



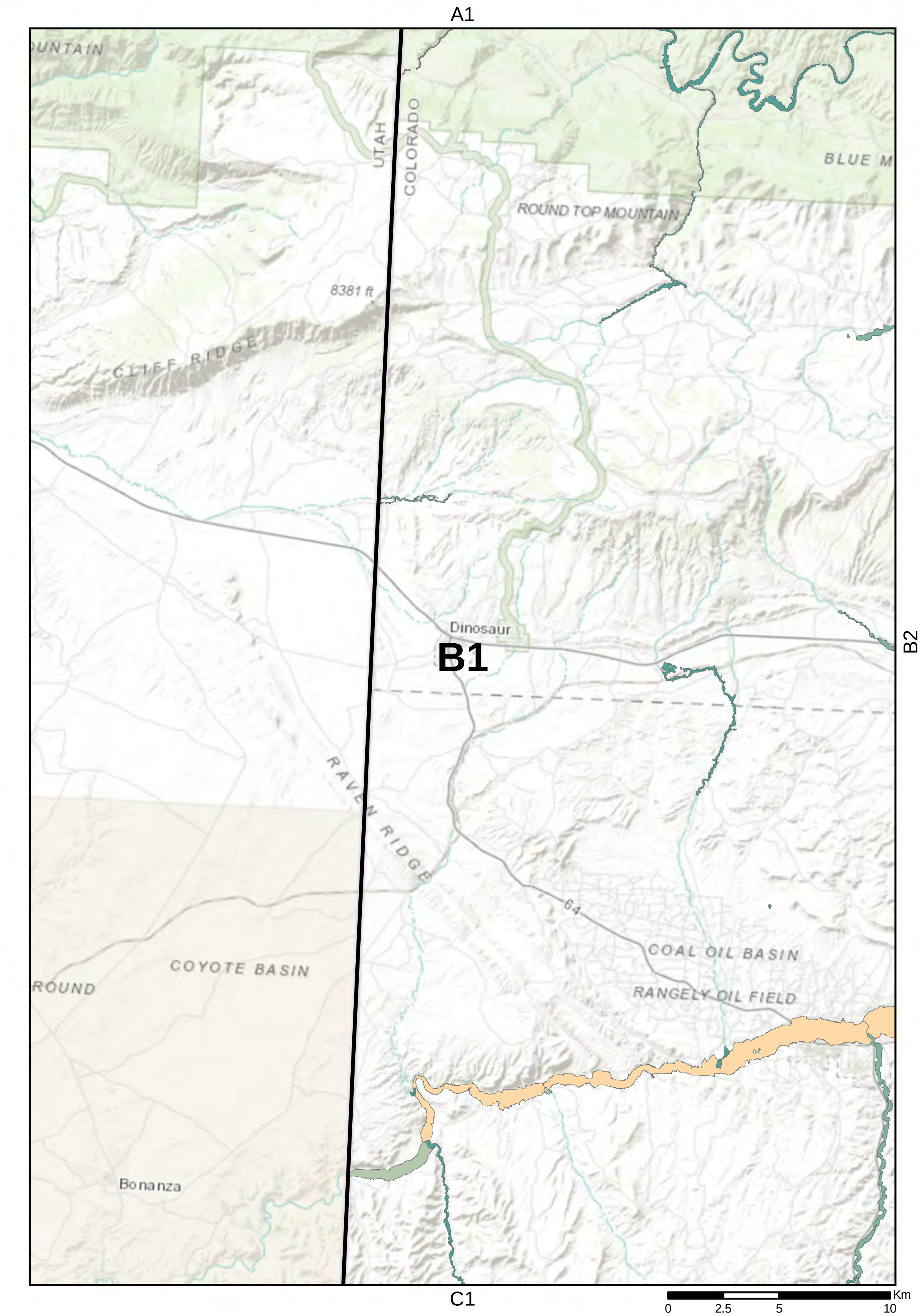
A16

B15

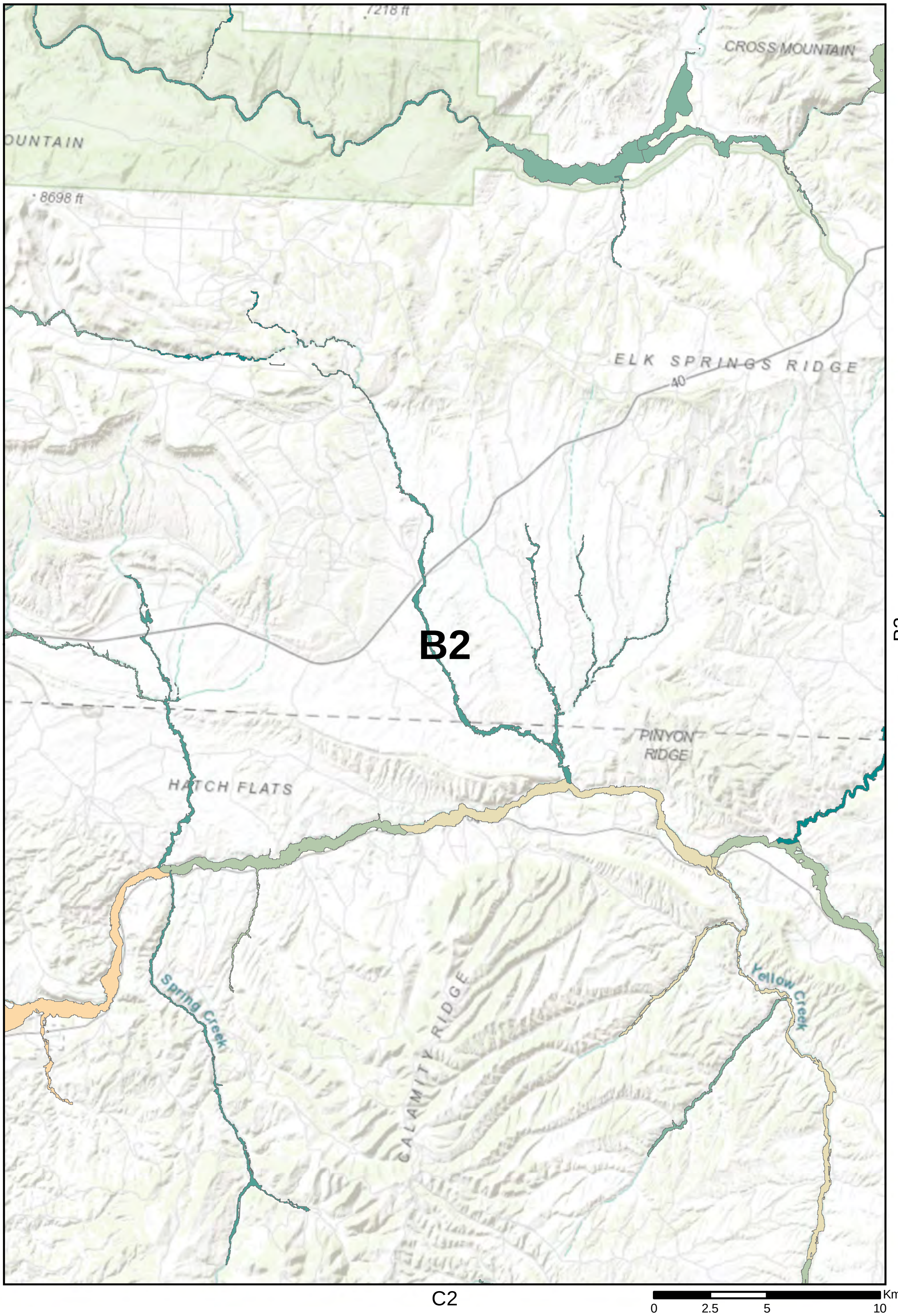
0 2.5 5 10 Km



80
ASKA
RADO
3608 ft
A16
A15
Venango
385
CK
Amherst
176
6
COLORADO
NEBRASKA
Lamar
B16
Km
0
2.5
5
10


A1
UNTAIN
UTAH
COLORADO
BLUE M
ROUND TOP MOUNTAIN
8381 ft
CLIFF RIDGE
Dinosaur
B1
B2
RAVEN RIDGE
64
COAL OIL BASIN
RANGELY OIL FIELD
COYOTE BASIN
ROUND
Bonanza
C1
0 2.5 5 10 Km

A2


7218 ft
CROSS MOUNTAIN
OUNTAIN
8698 ft
ELK SPRINGS RIDGE
40
B2
PINYON RIDGE
HATCH FLATS
Spring Creek
CALAMITY RIDGE
Yellow Creek
0
2.5
5
10
Km

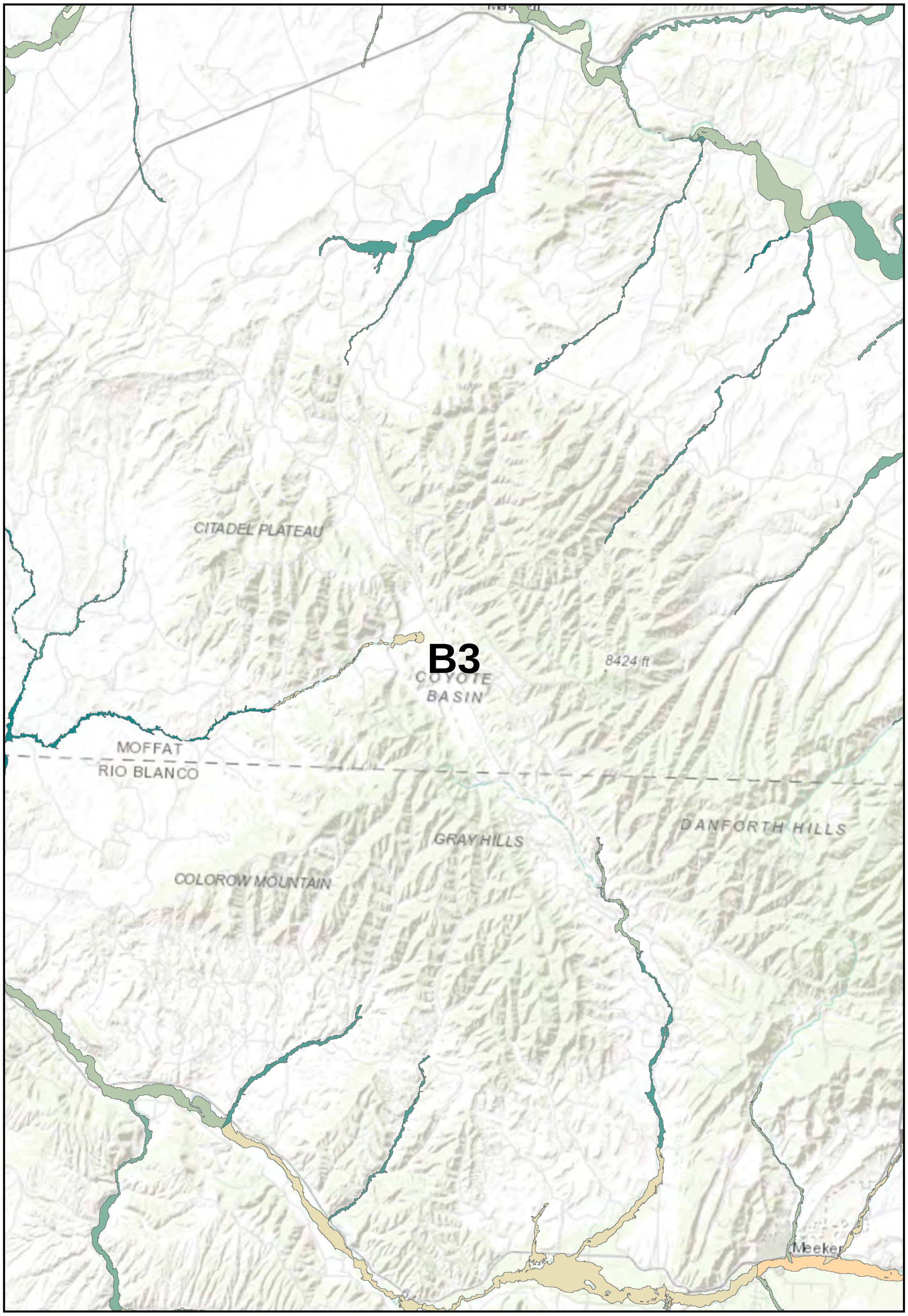
B1

B3

C2

A3

B2

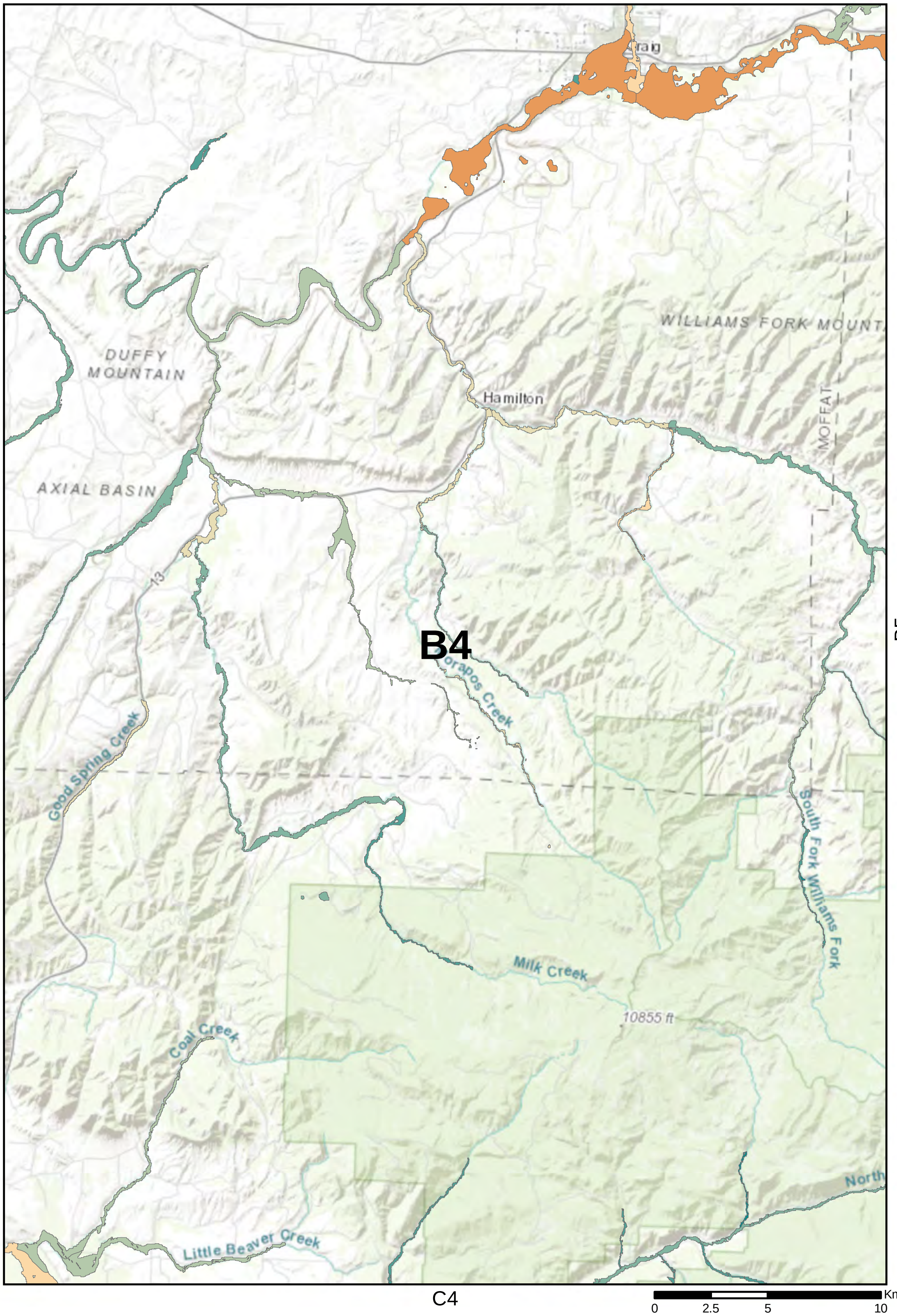


B4

C3

0 2.5 5 10 Km

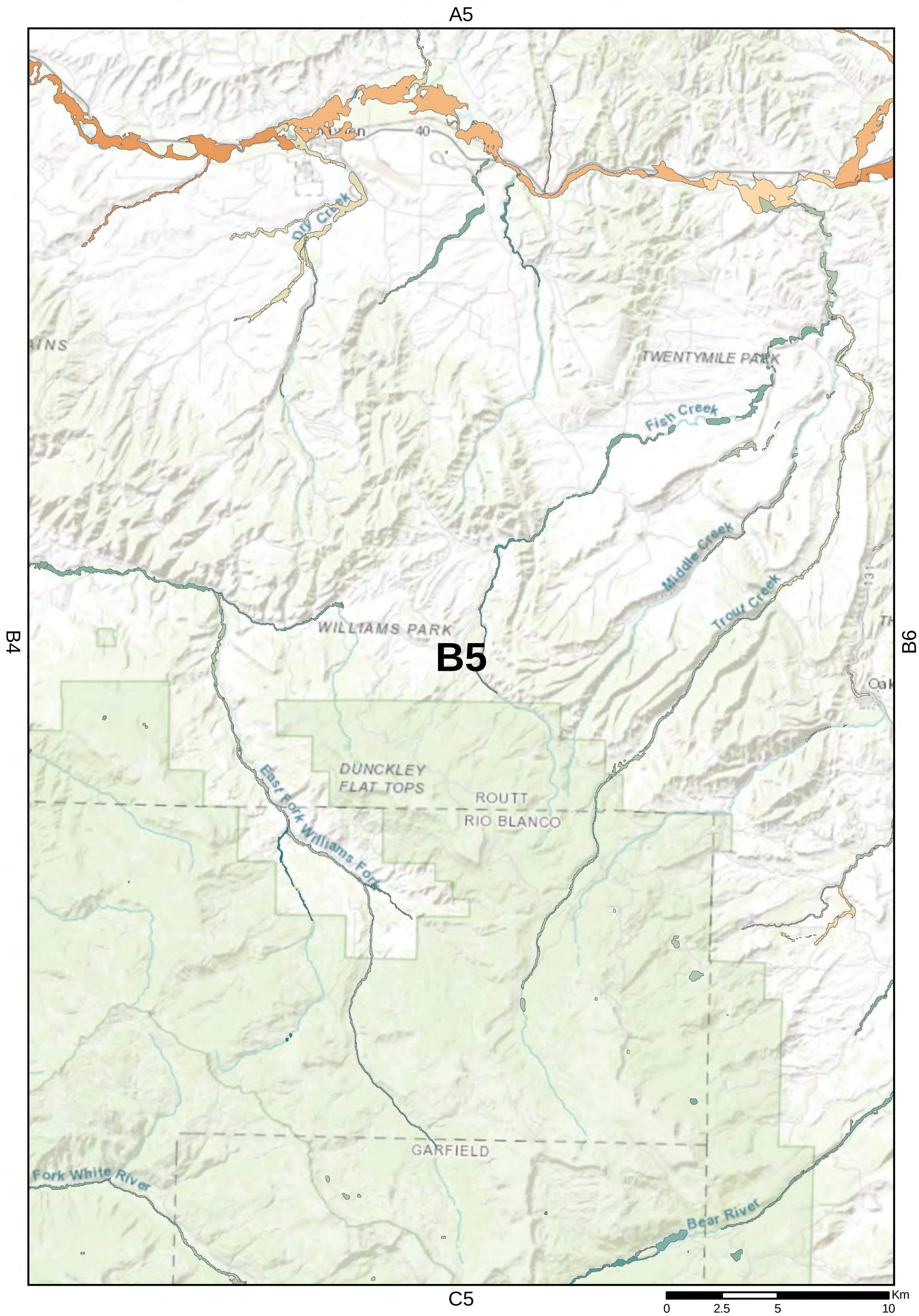
A4


Craig
DUFFY MOUNTAIN
WILLIAMS FORK MOUNT
Hamilton
AXIAL BASIN
MOFFAT
13
B4
Good Spring Creek
South Fork Williams Fork
Milk Creek
10855 ft
Coal Creek
Little Beaver Creek
North
0
2.5
5
10
Km

B3

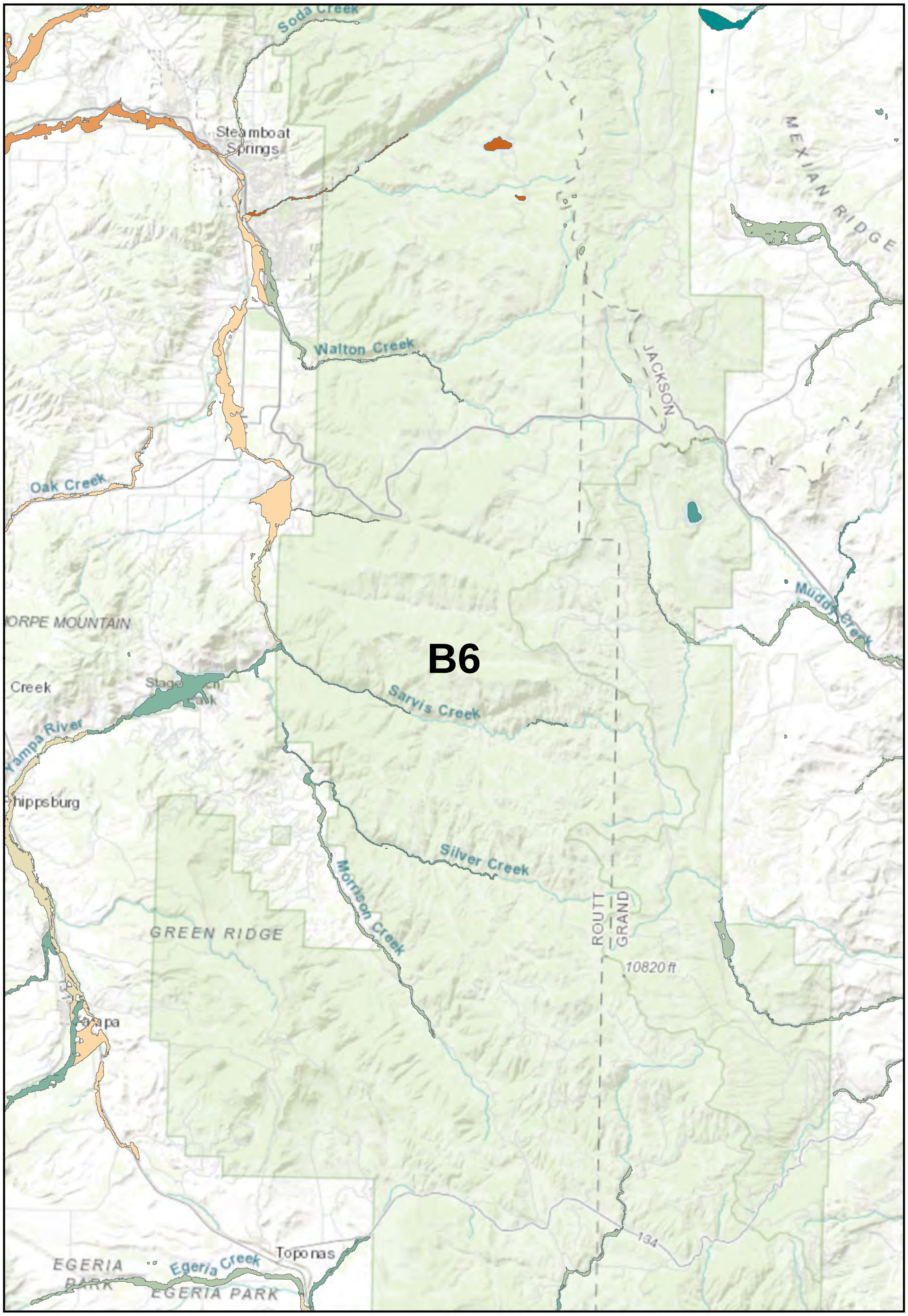
B5

C4


A5
B4
B5
B6
C5
40
Dry Creek
TWENTYMILE PARK
Fish Creek
Middle Creek
Trout Creek
131
WILLIAMS PARK
DUNCKLEY
FLAT TOPS
ROUTT
RIO BLANCO
East Fork Williams Fork
GARFIELD
Fork White River
Bear River
0
2.5
5
10
Km

A6

B5

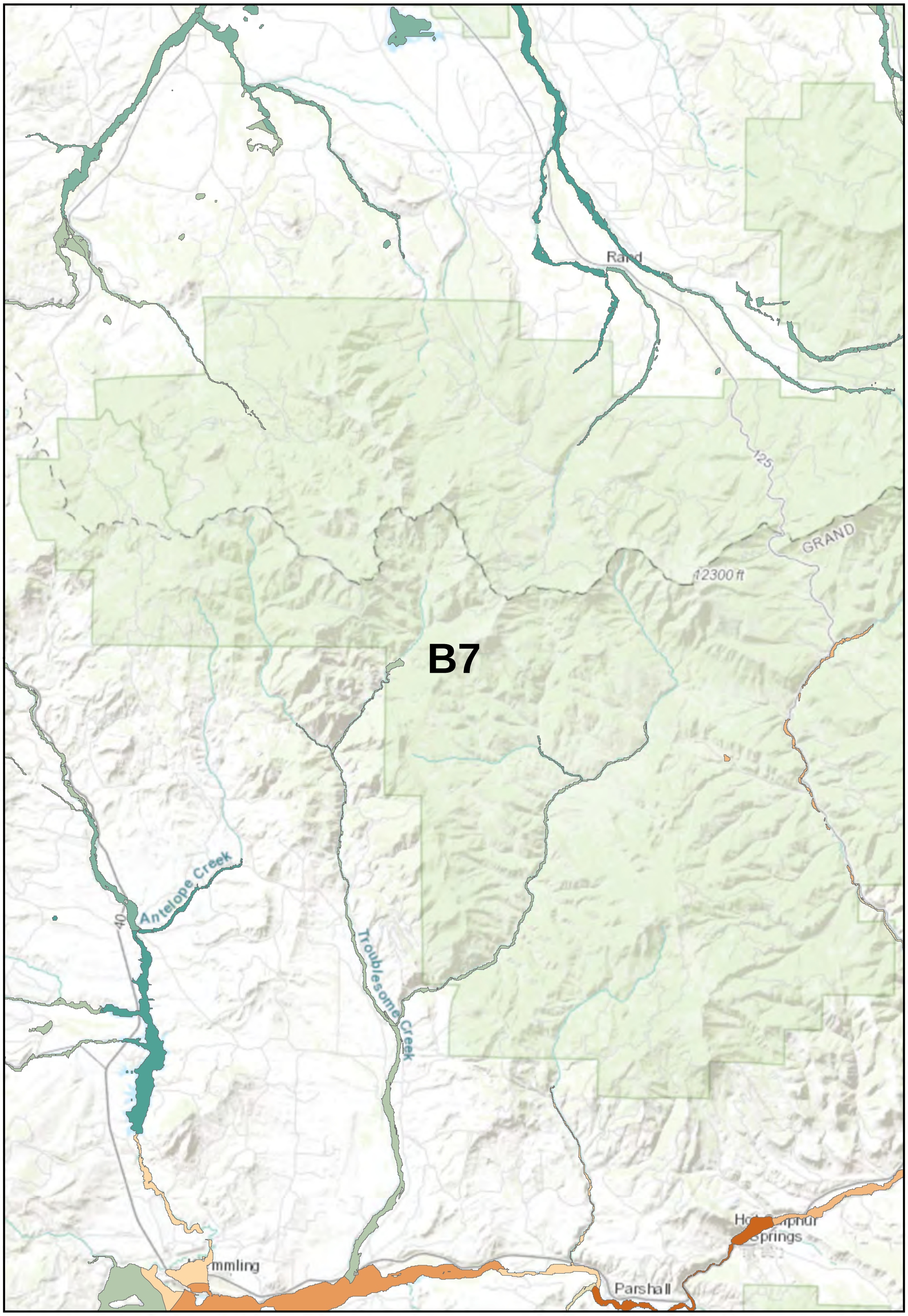


B7

C6

0 2.5 5 10 Km

A7



B6

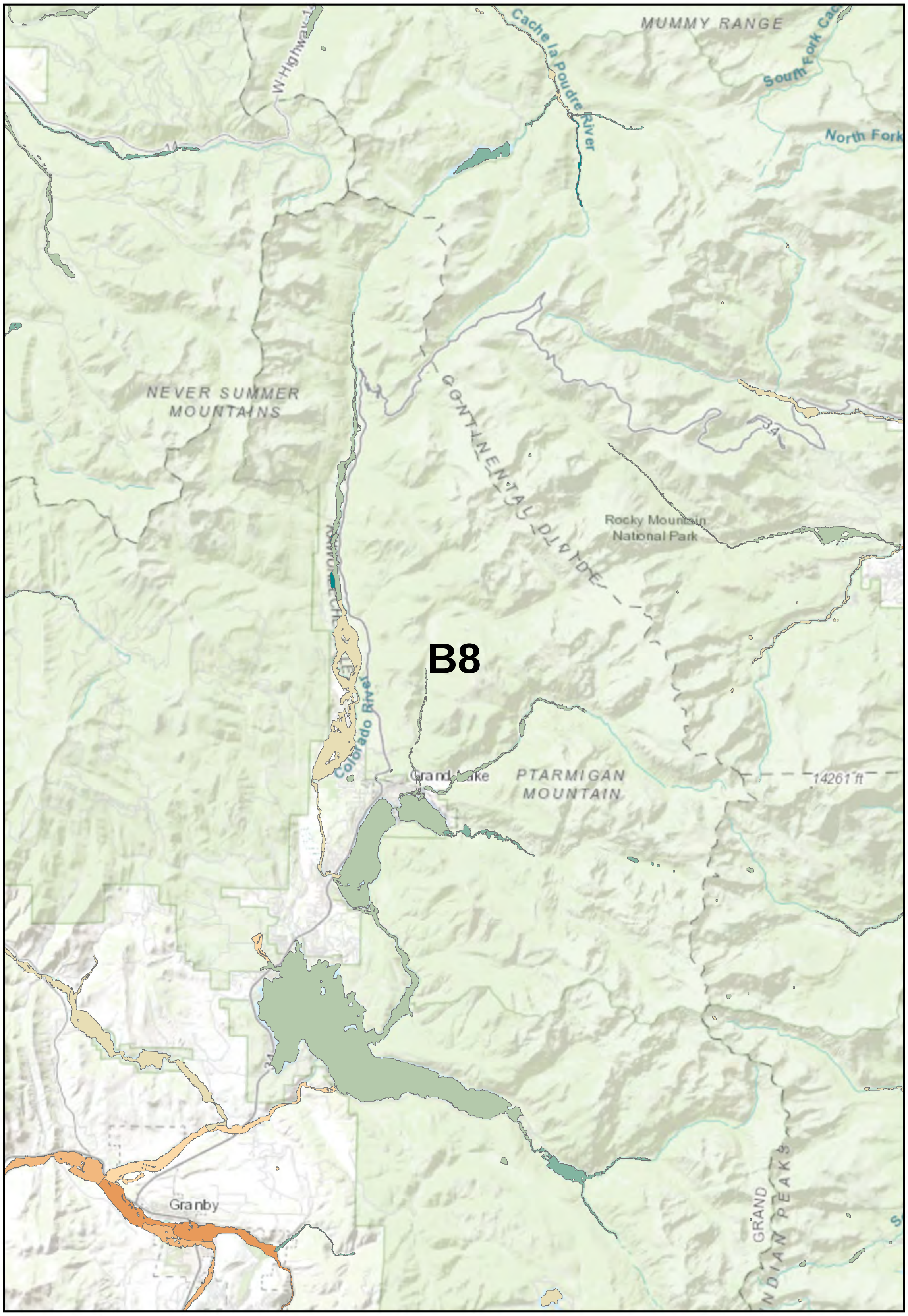
B8

C7

0 2.5 5 10 Km

A8

B7

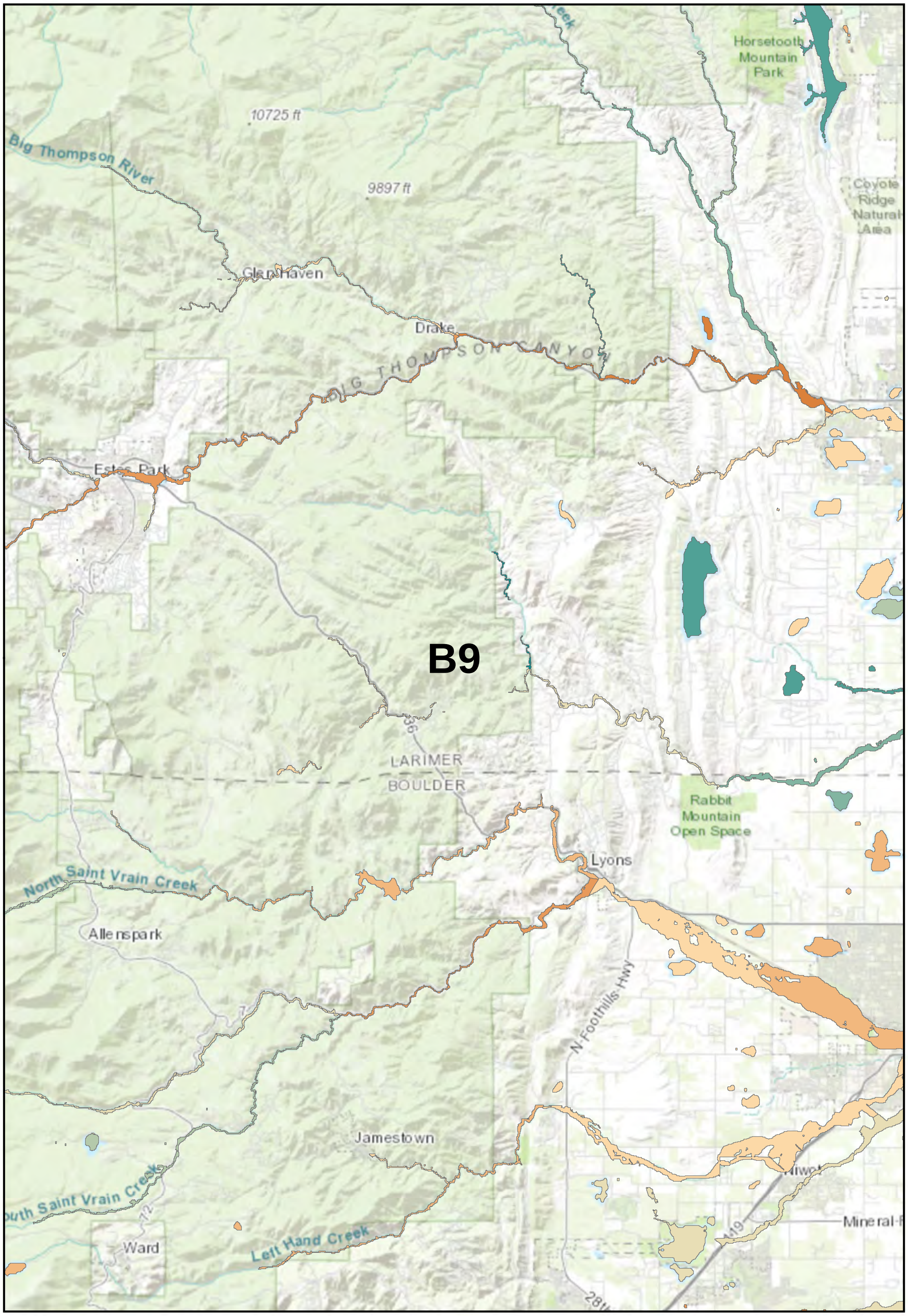


B9

C8

0 2.5 5 10 Km

A9



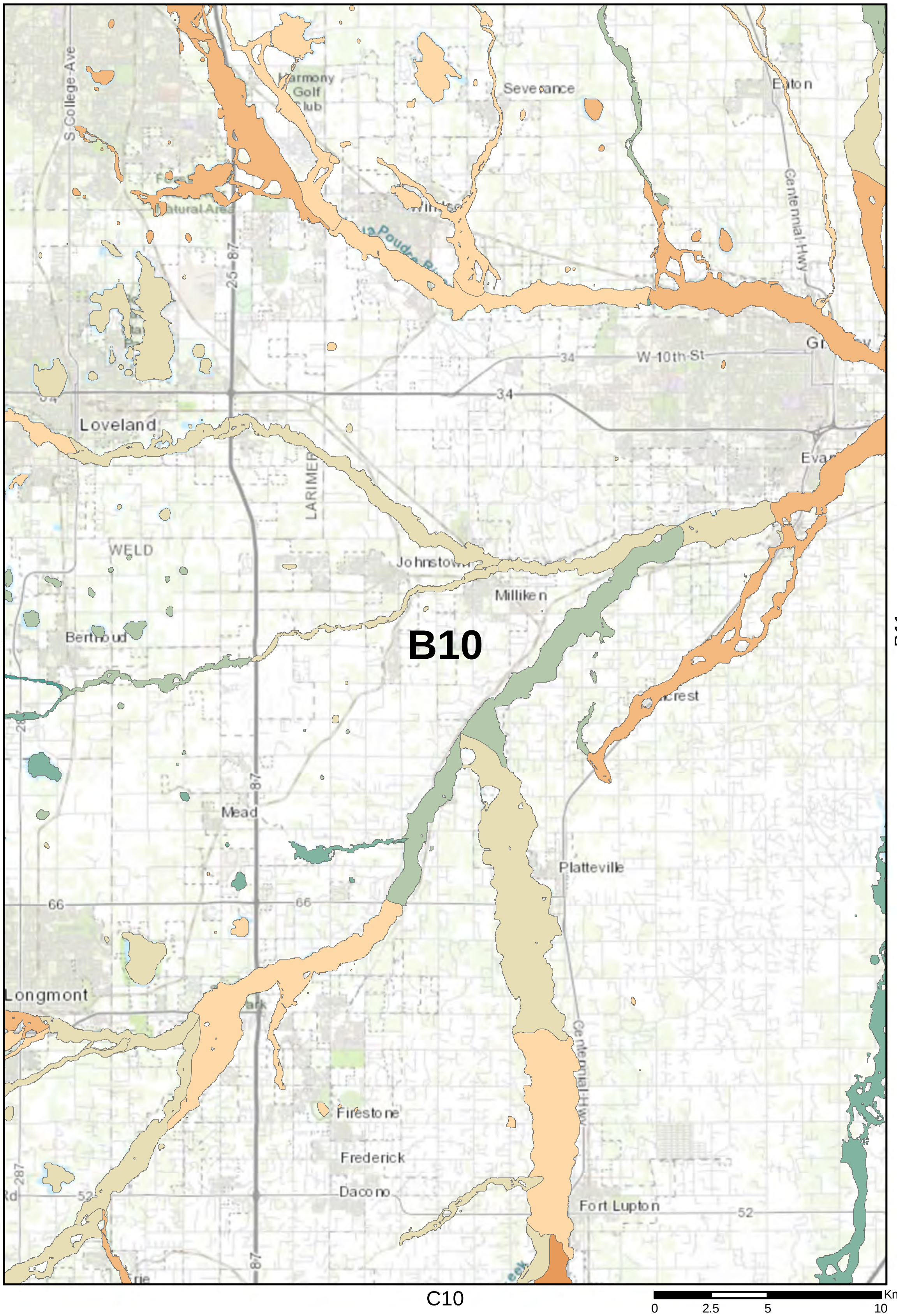
B8

B10

C9

0 2.5 5 10 Km

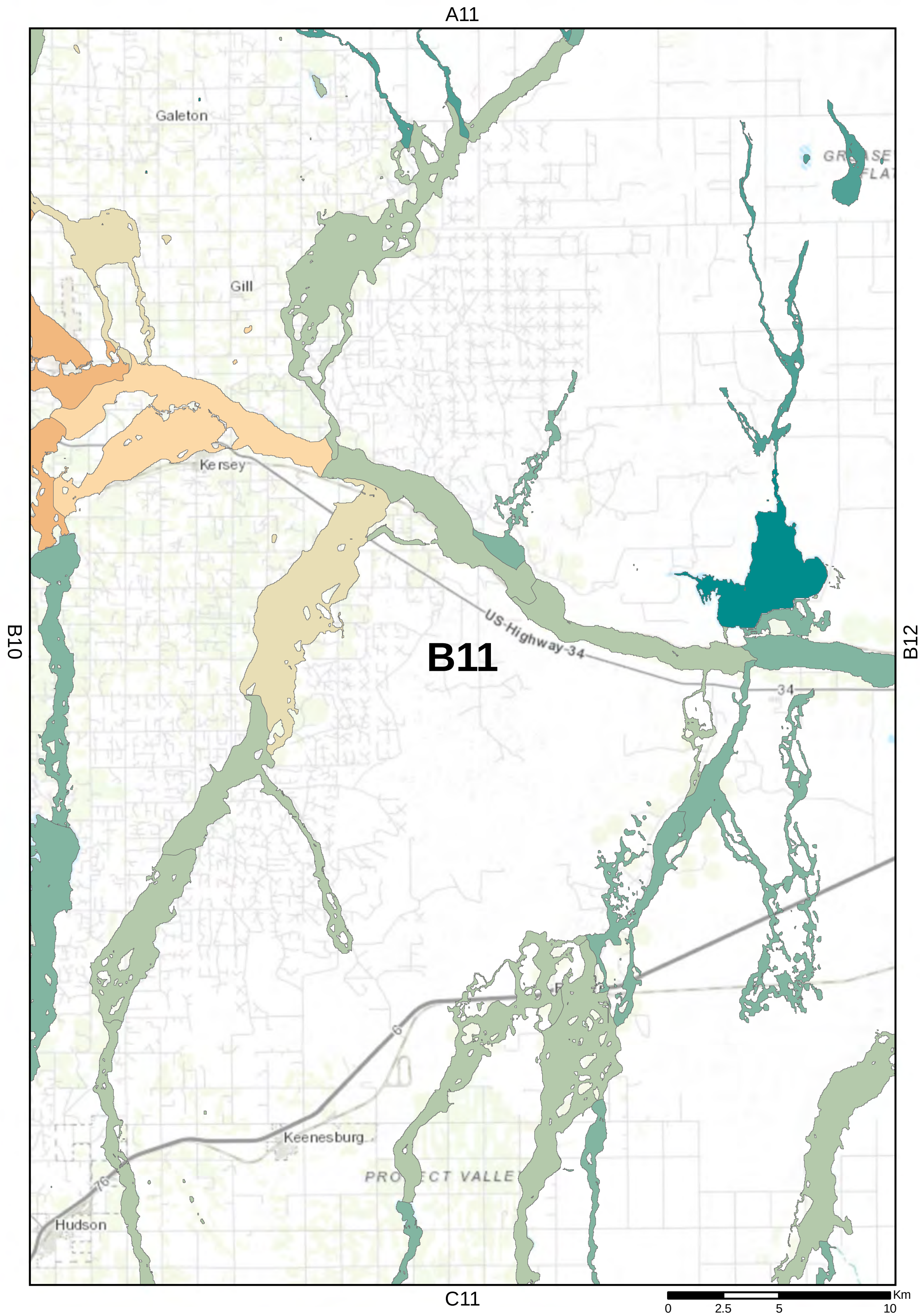
A10



B9

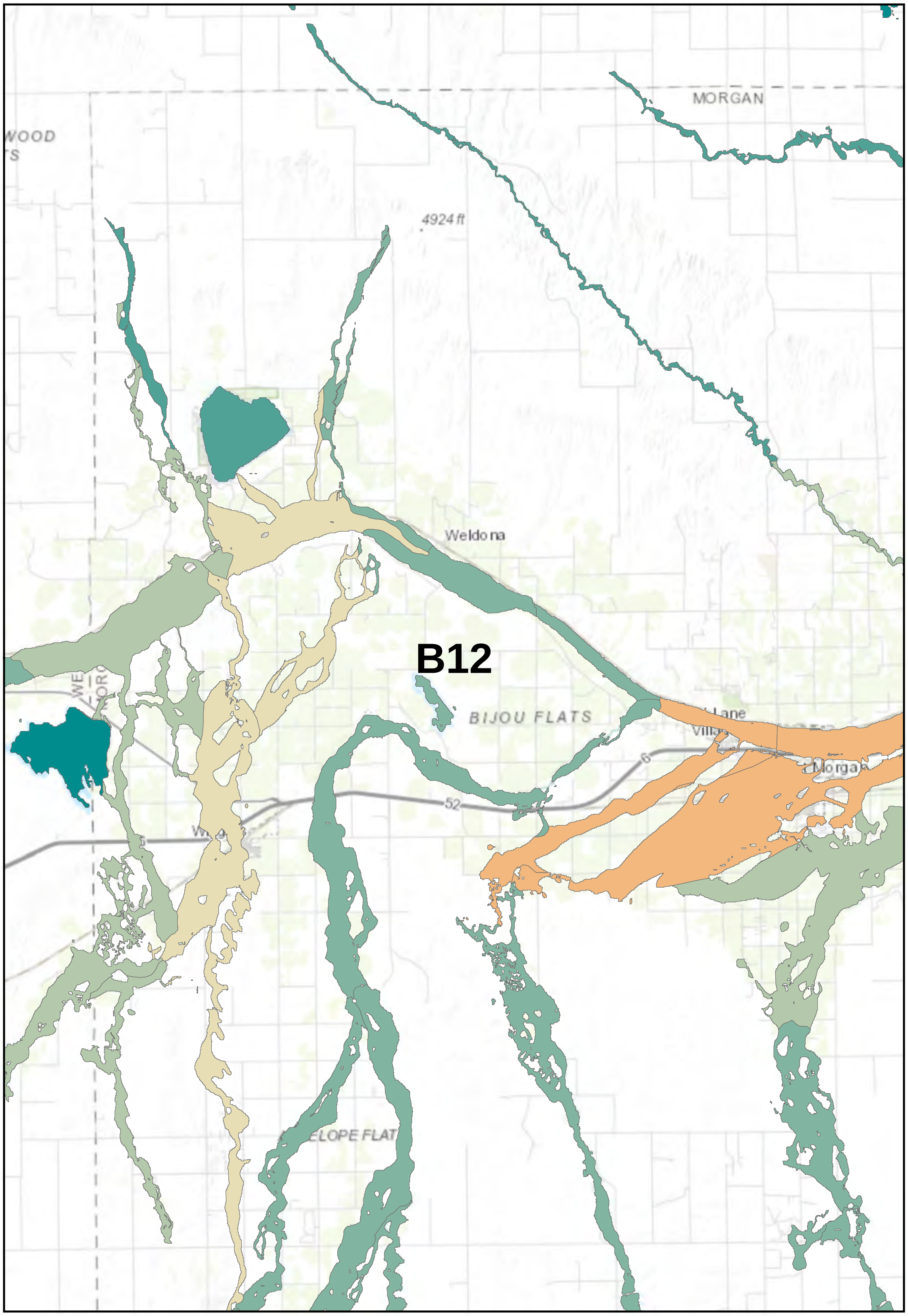
B11

C10


A11
B10
B12
C11
B11
Galeton
Gill
Kersey
US-Highway-34
34
6
76
Keenesburg
Hudson
Km
0
2.5
5
10

A12

B11

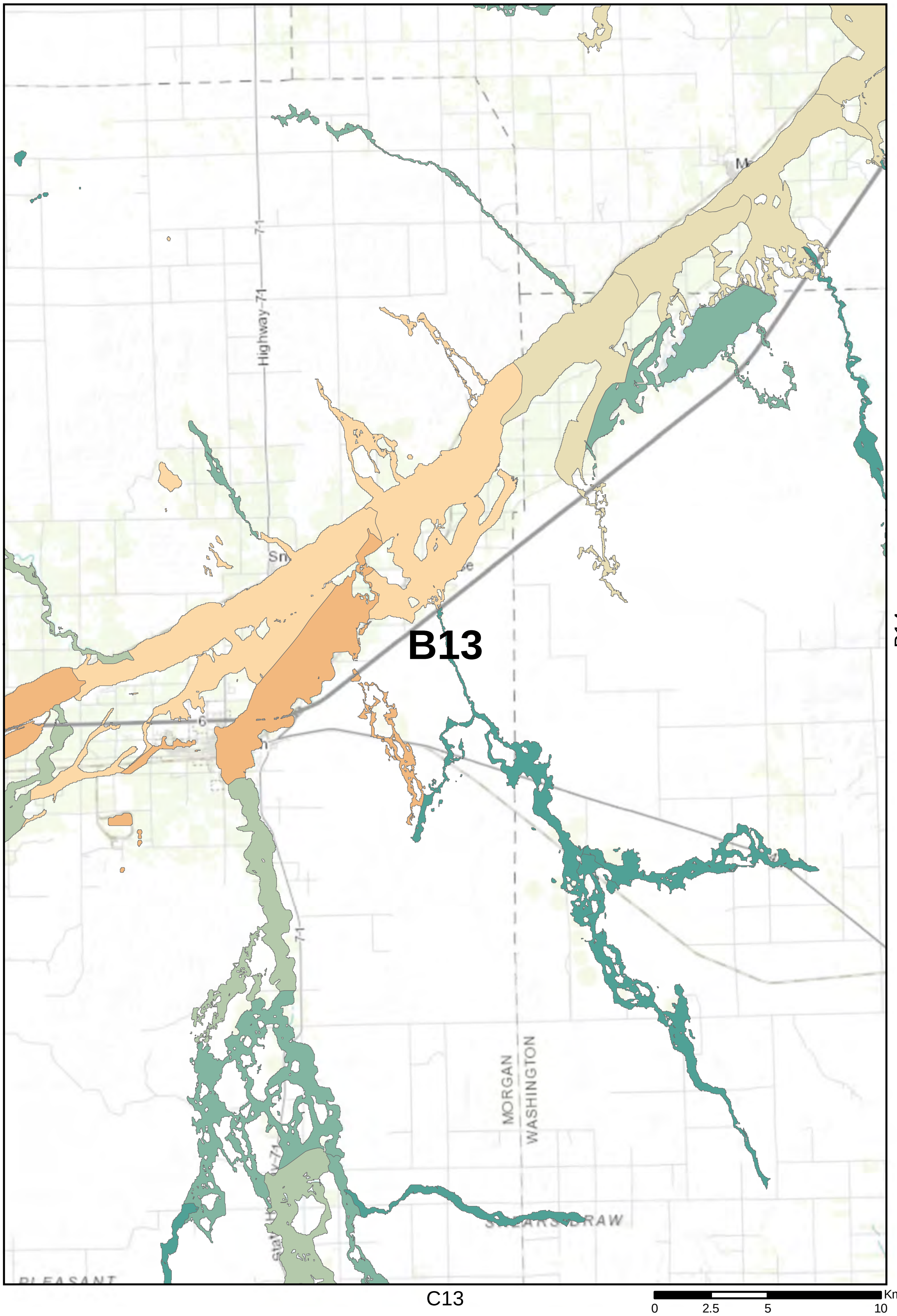


B13

C12

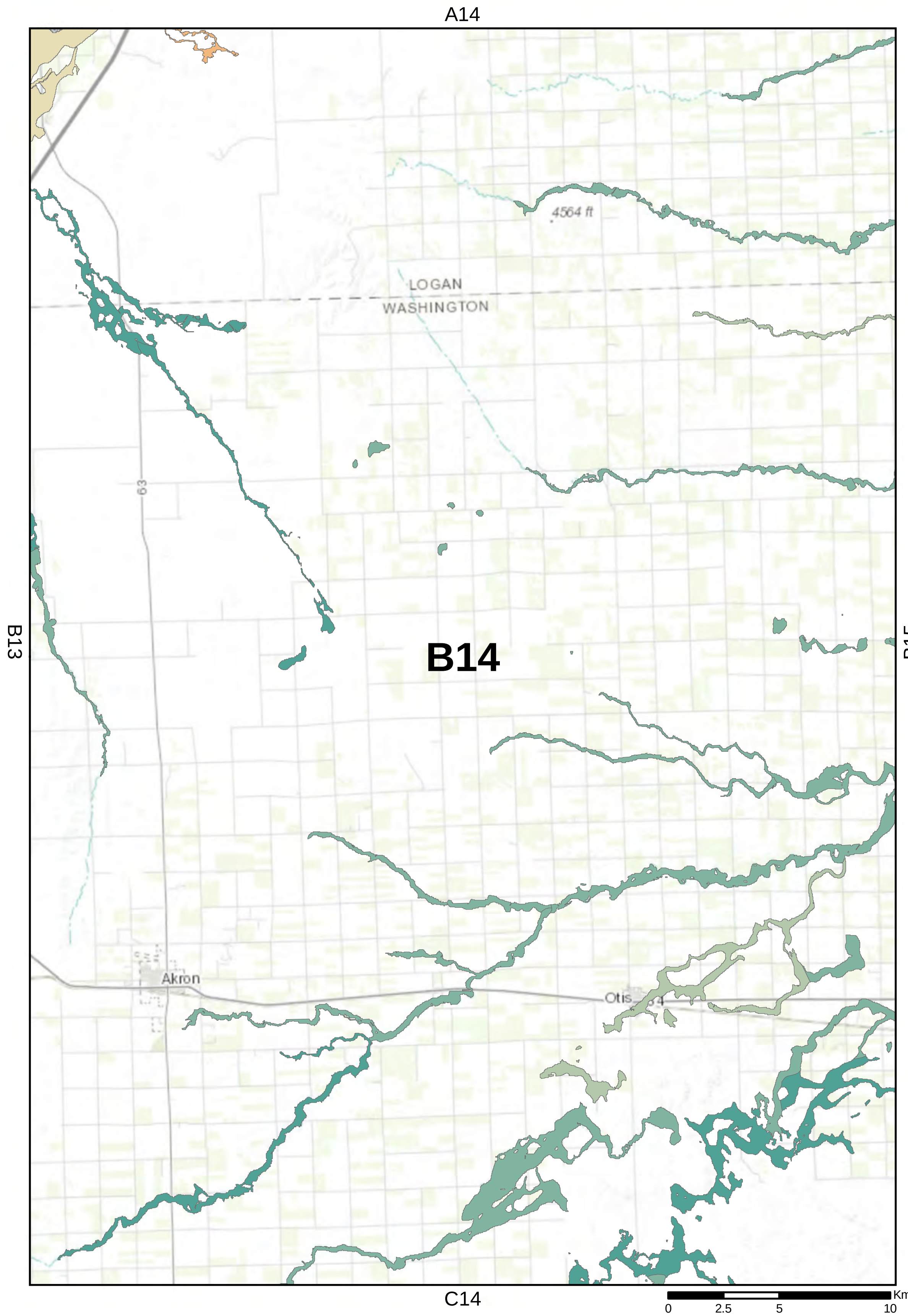
A13

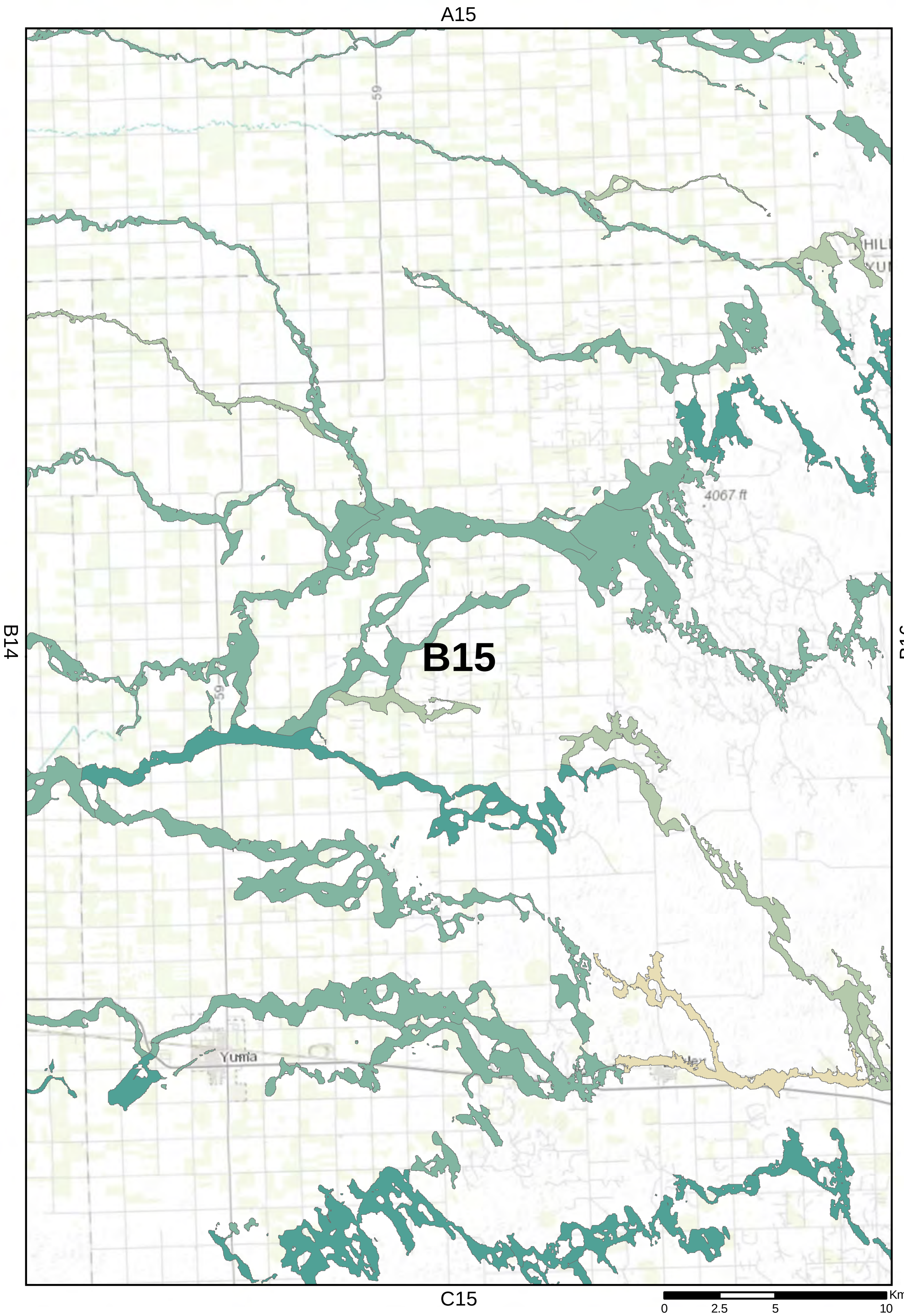
B12

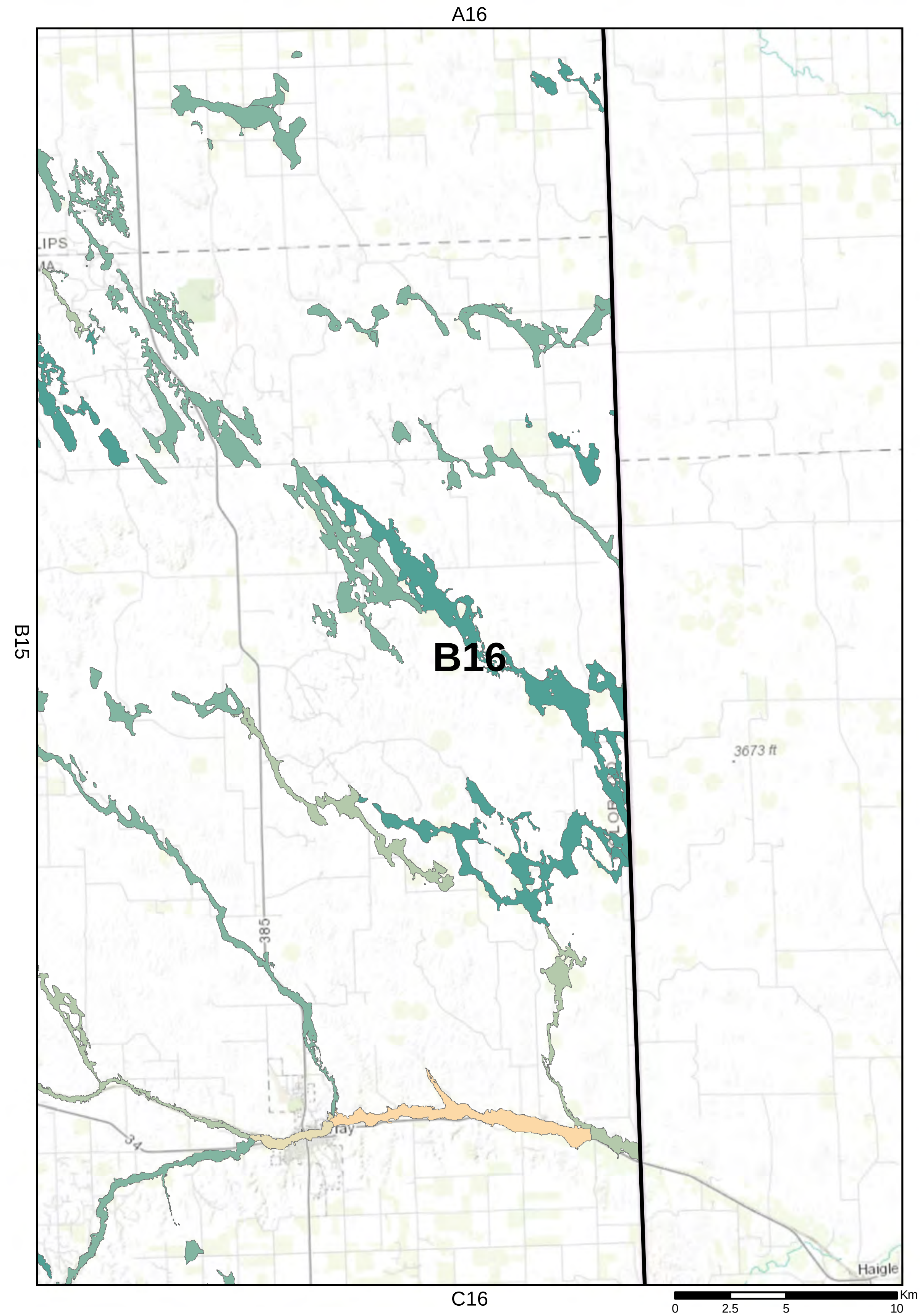


B14

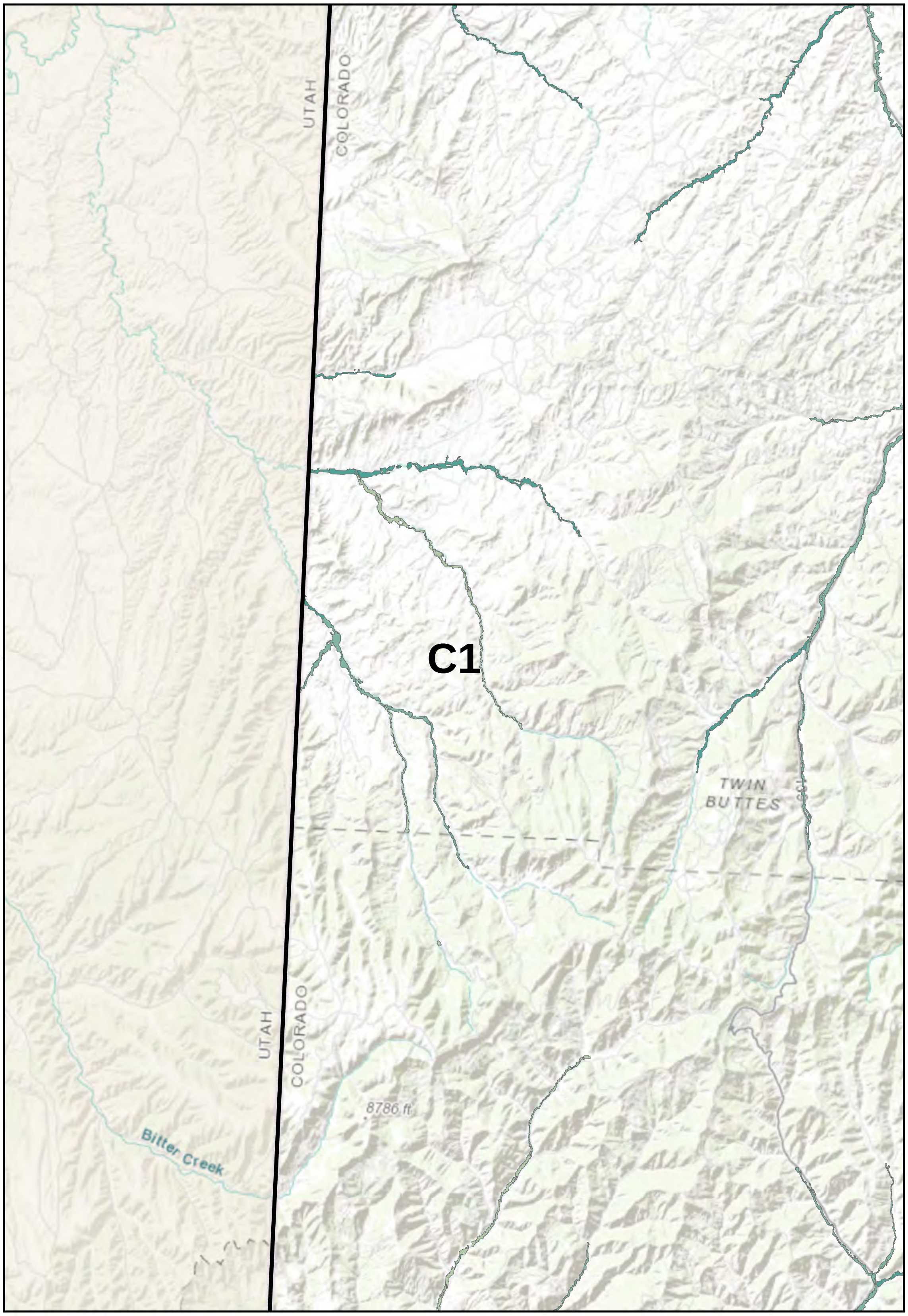
C13


A14
B13
B14
B15
C14
LOGAN
WASHINGTON
4564 ft
63
Akron
Otis
Km
0
2.5
5
10


A15
B14
B15
B16
C15
4067 ft
Yuma
Km
0
2.5
5
10


A16
B15
B16
C16
3673 ft
385
34
Haigle
0
2.5
5
10
Km

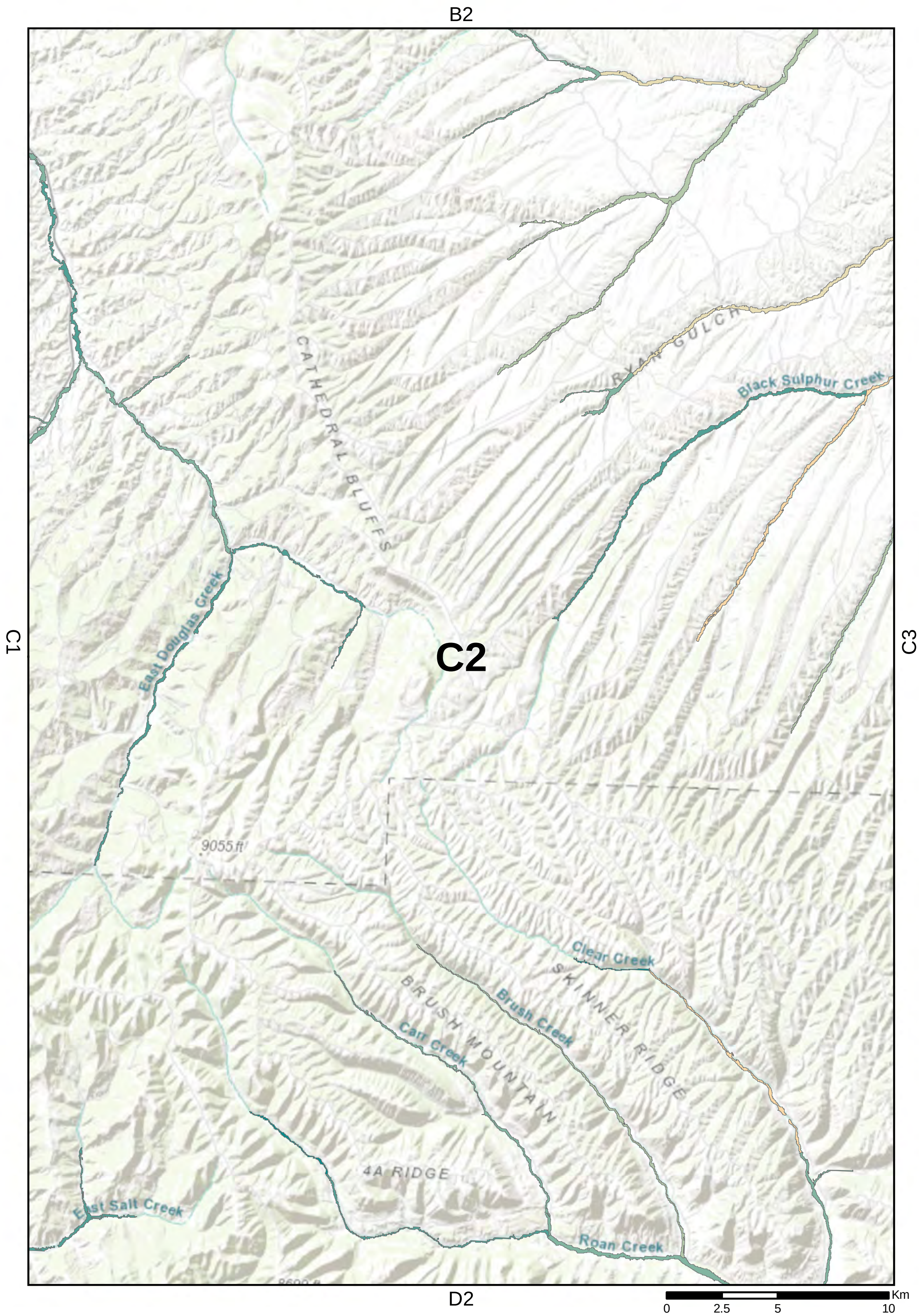
B1



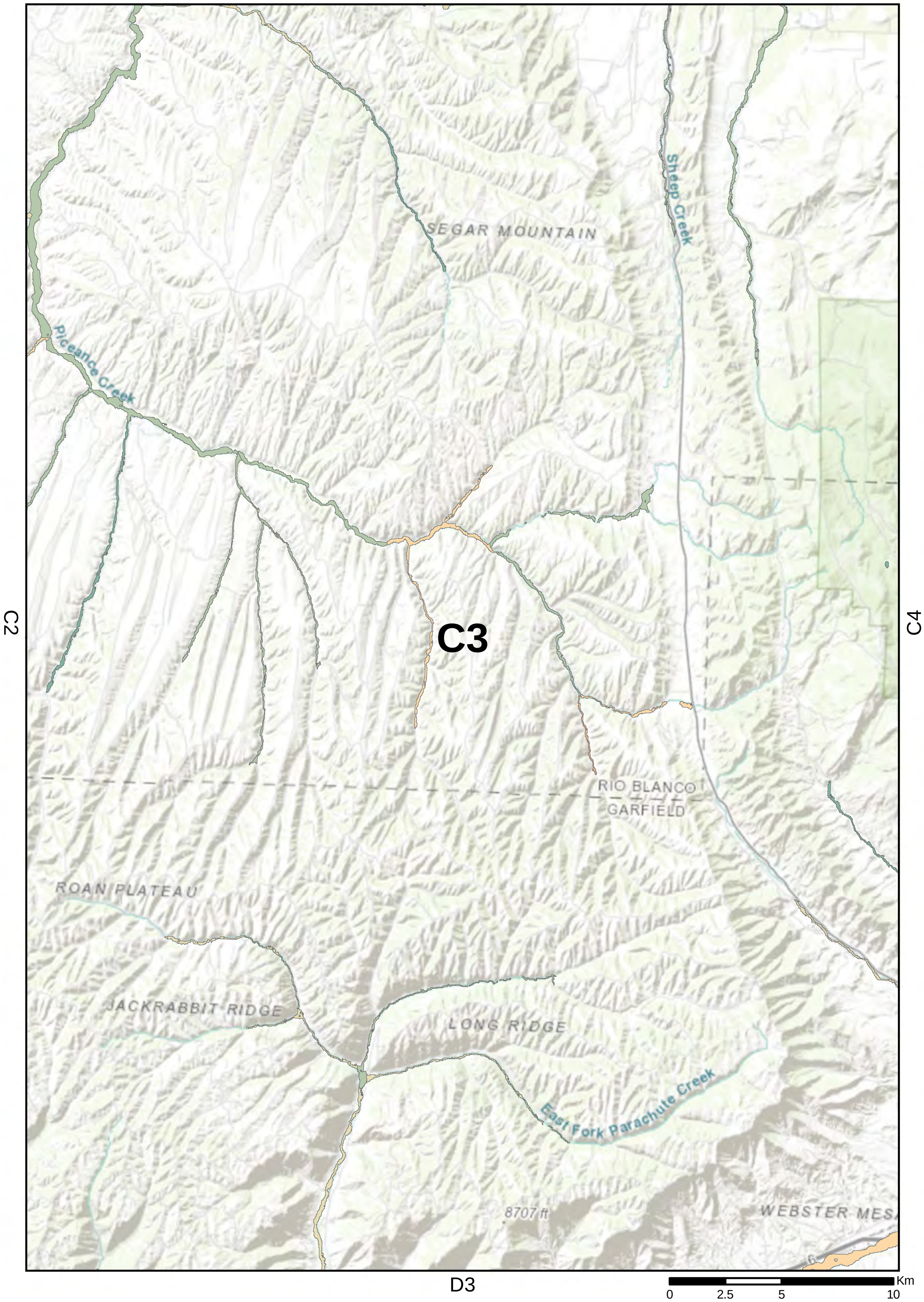
C2

D1

0 2.5 5 10 Km


B2
C1
C2
C3
D2
CATHEDRAL BLUFFS
RYAN GULCH
Black Sulphur Creek
East Douglas Creek
9055 ft
Clear Creek
SKINNER RIDGE
BRUSH MOUNTAIN
Brush Creek
Carr Creek
4A RIDGE
East Salt Creek
Roan Creek
0
2.5
5
10
Km

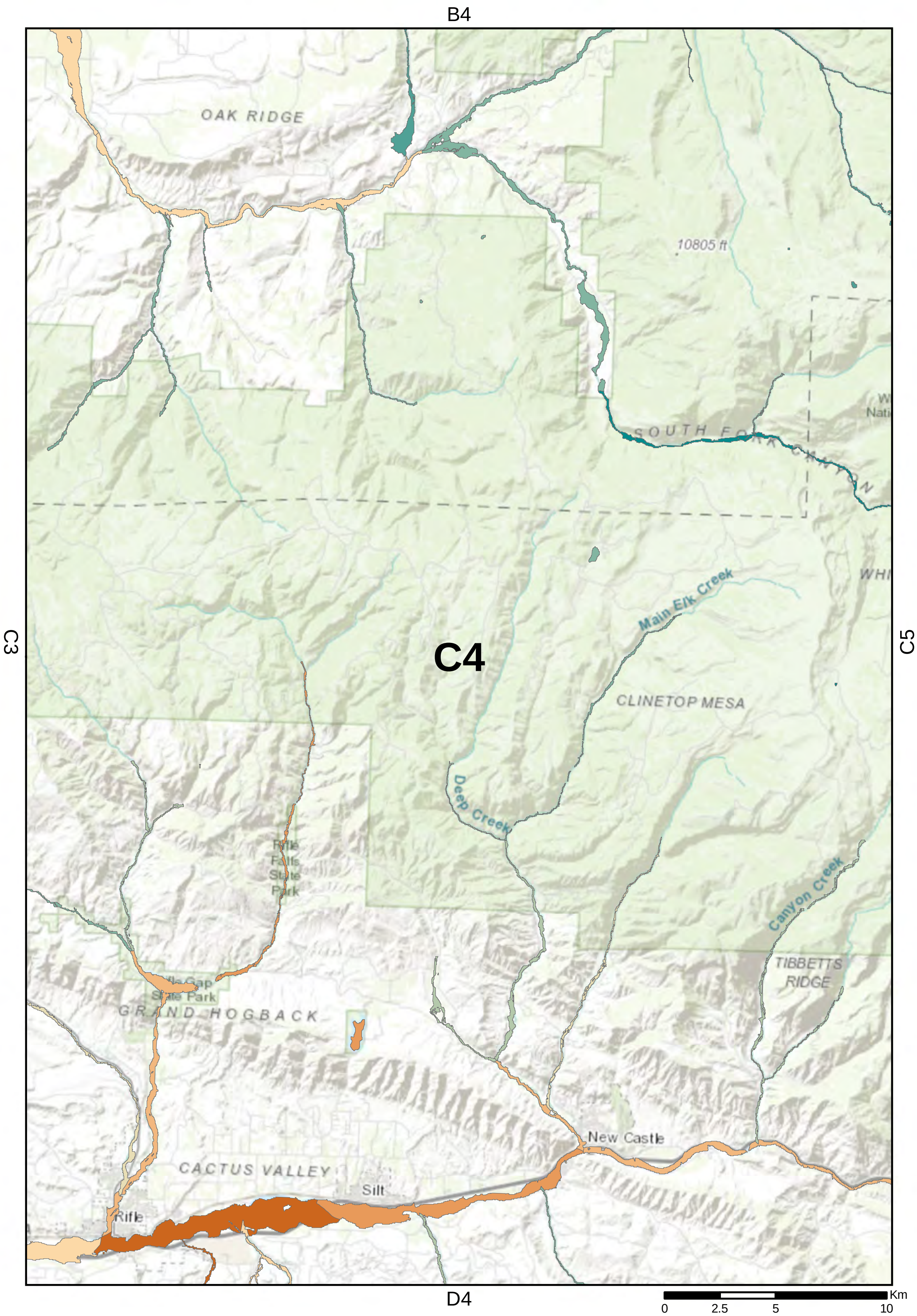
B3



SEGAR MOUNTAIN
Sheep Creek
Piceance Creek
C2
C3
C4
RIO BLANCO
GARFIELD
ROAN PLATEAU
JACKRABBIT RIDGE
LONG RIDGE
East Fork Parachute Creek
8707 ft
WEBSTER MES

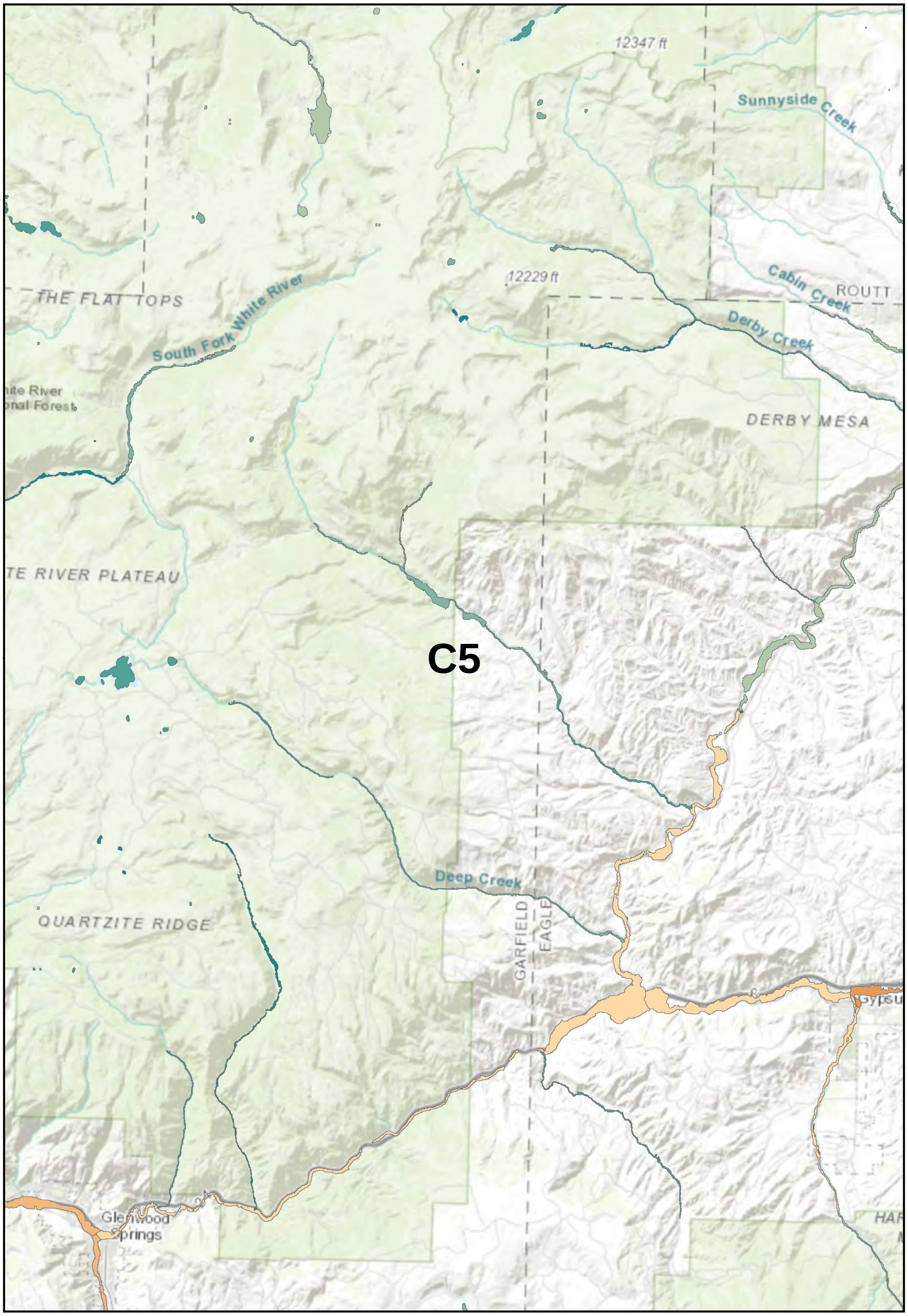
D3

Km
0 2.5 5 10


B4
C3
C5
D4
C4
OAK RIDGE
10805 ft
SOUTH FORK CANYON
Main Elk Creek
CLINETOP MESA
Deep Creek
Rifle Falls State Park
Canyon Creek
TIBBETTS RIDGE
GRAND HOGBACK
New Castle
CACTUS VALLEY
Silt
Rifle
Km
0
2.5
5
10

B5

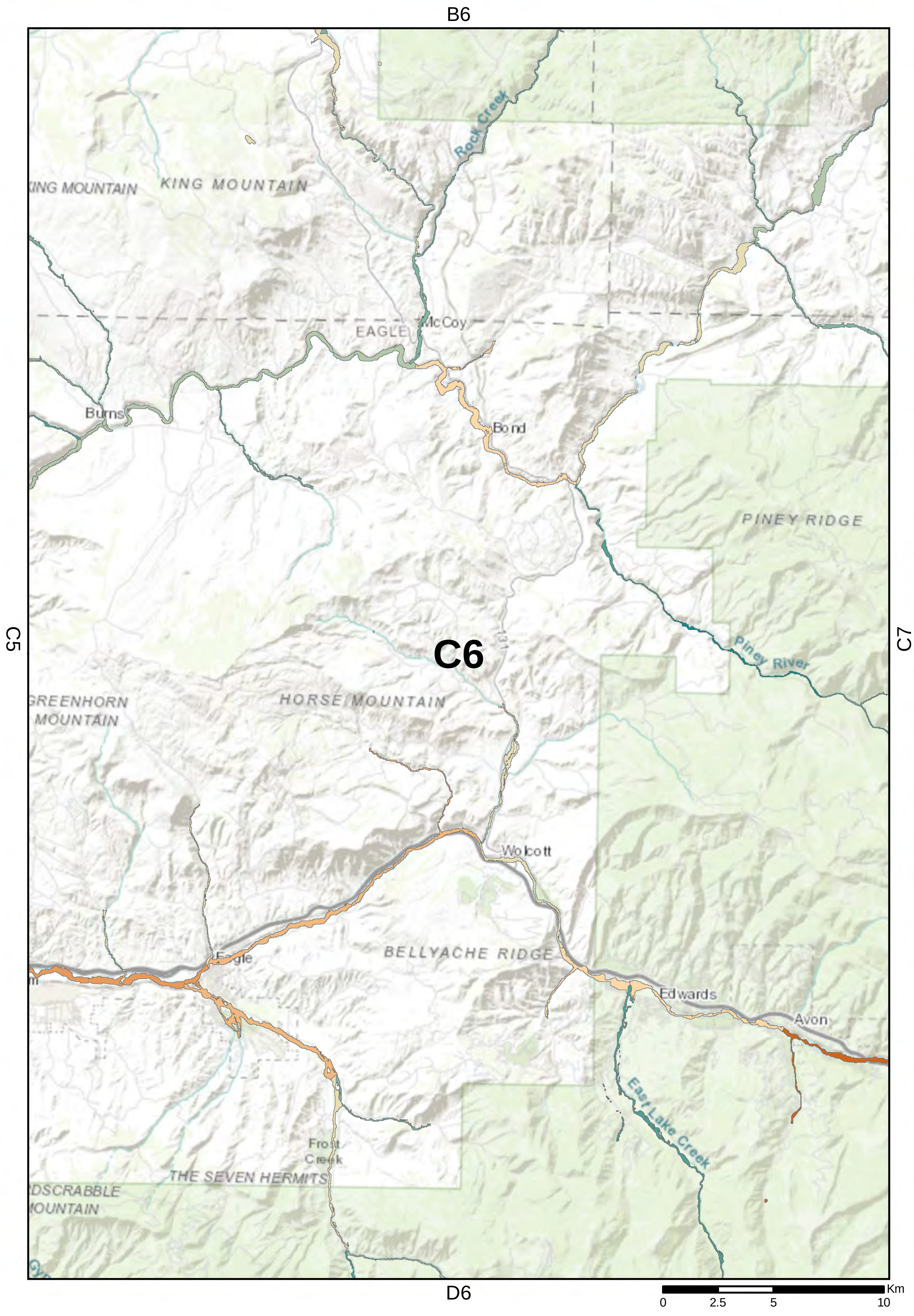
C4



C6

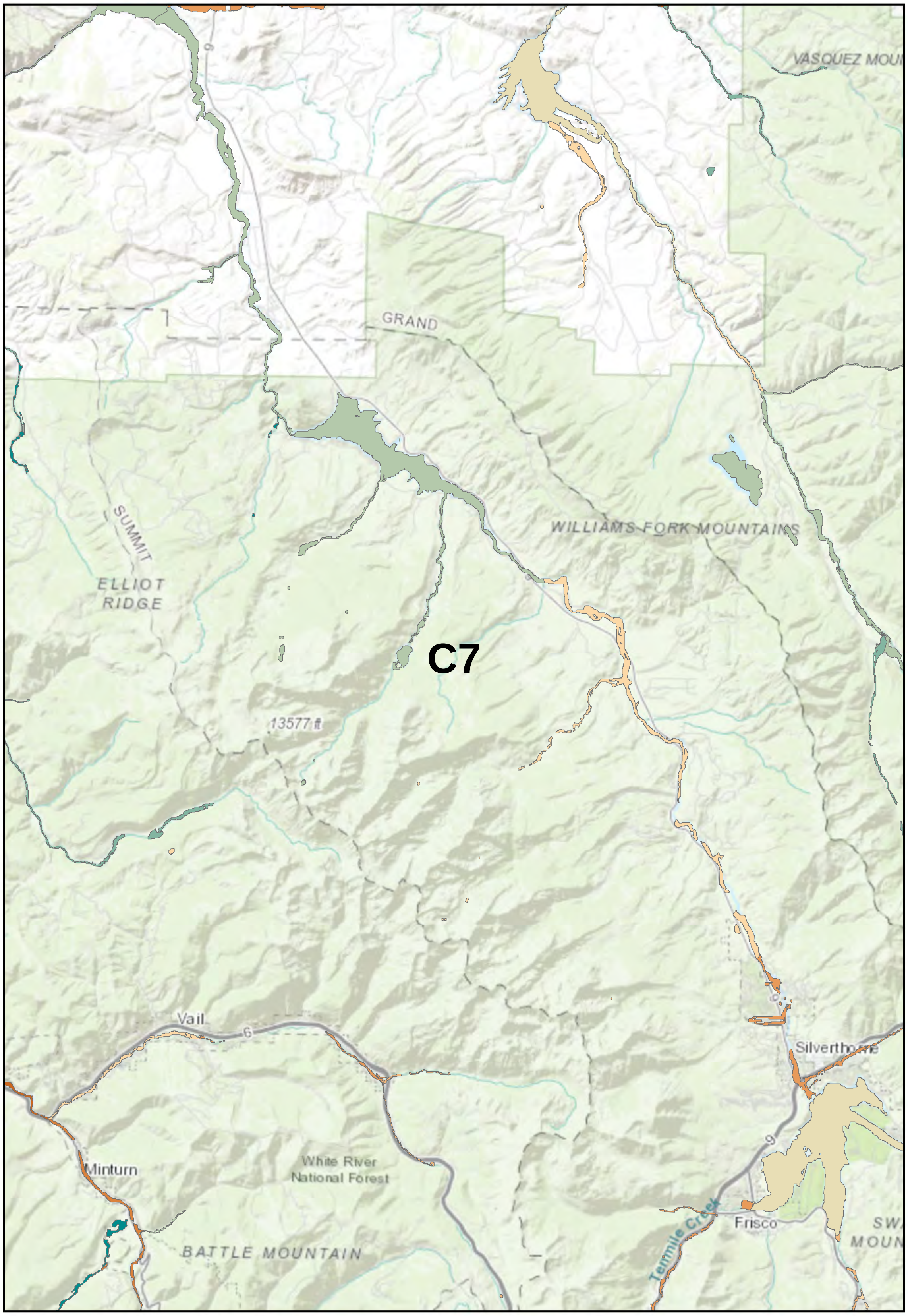
D5

Km
0 2.5 5 10


B6
C5
C6
C7
D6
Rock Creek
KING MOUNTAIN
KING MOUNTAIN
EAGLE
McCoy
Burns
Bond
PINEY RIDGE
Piney River
131
GREENHORN MOUNTAIN
HORSE MOUNTAIN
Wolcott
BELLYACHE RIDGE
Eagle
Edwards
Avon
East Lake Creek
Frost Creek
THE SEVEN HERMITS
MOUNTAIN
Km
0
2.5
5
10

B7

C6



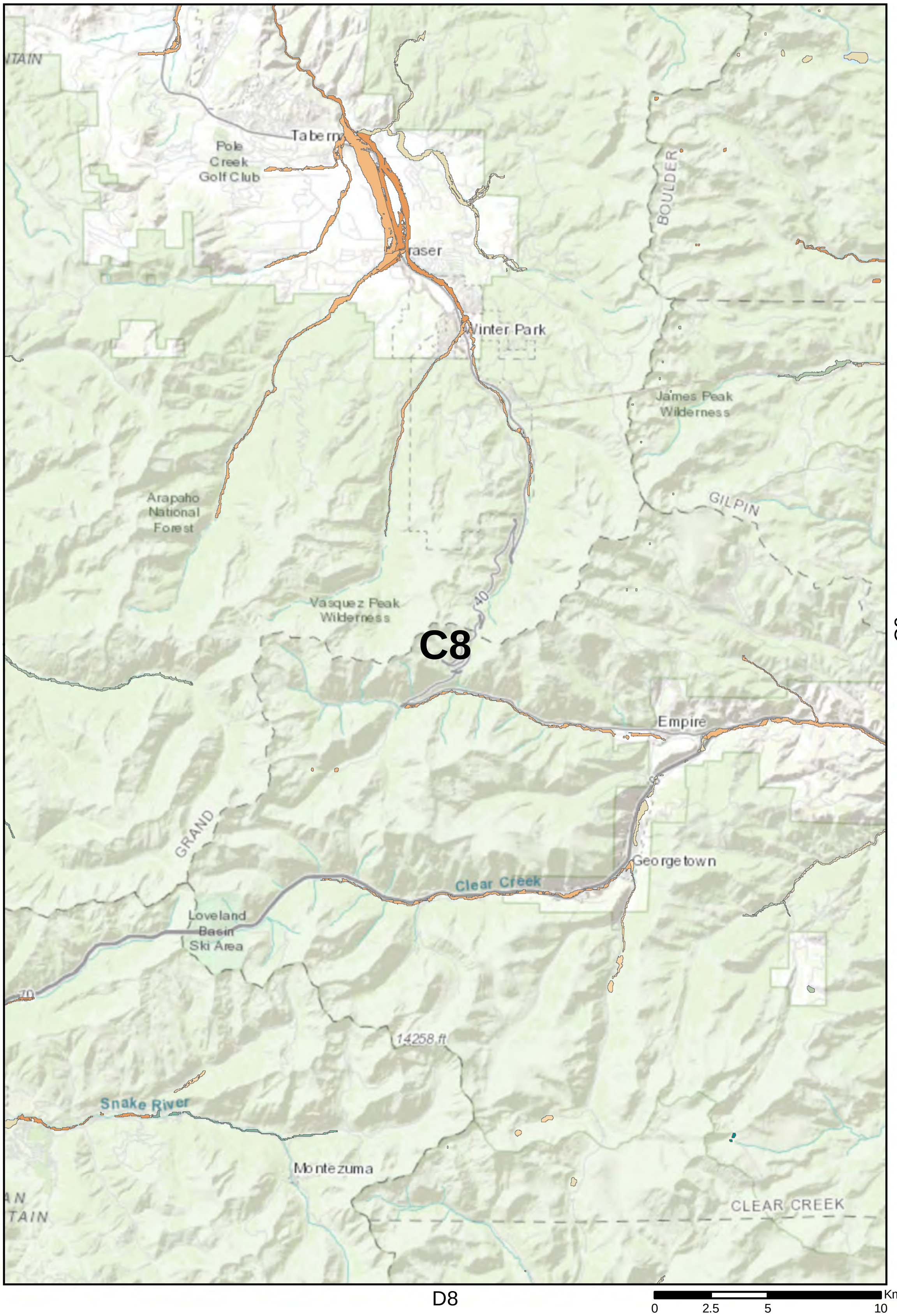
C8

D7

0 2.5 5 10 Km

B8

C7

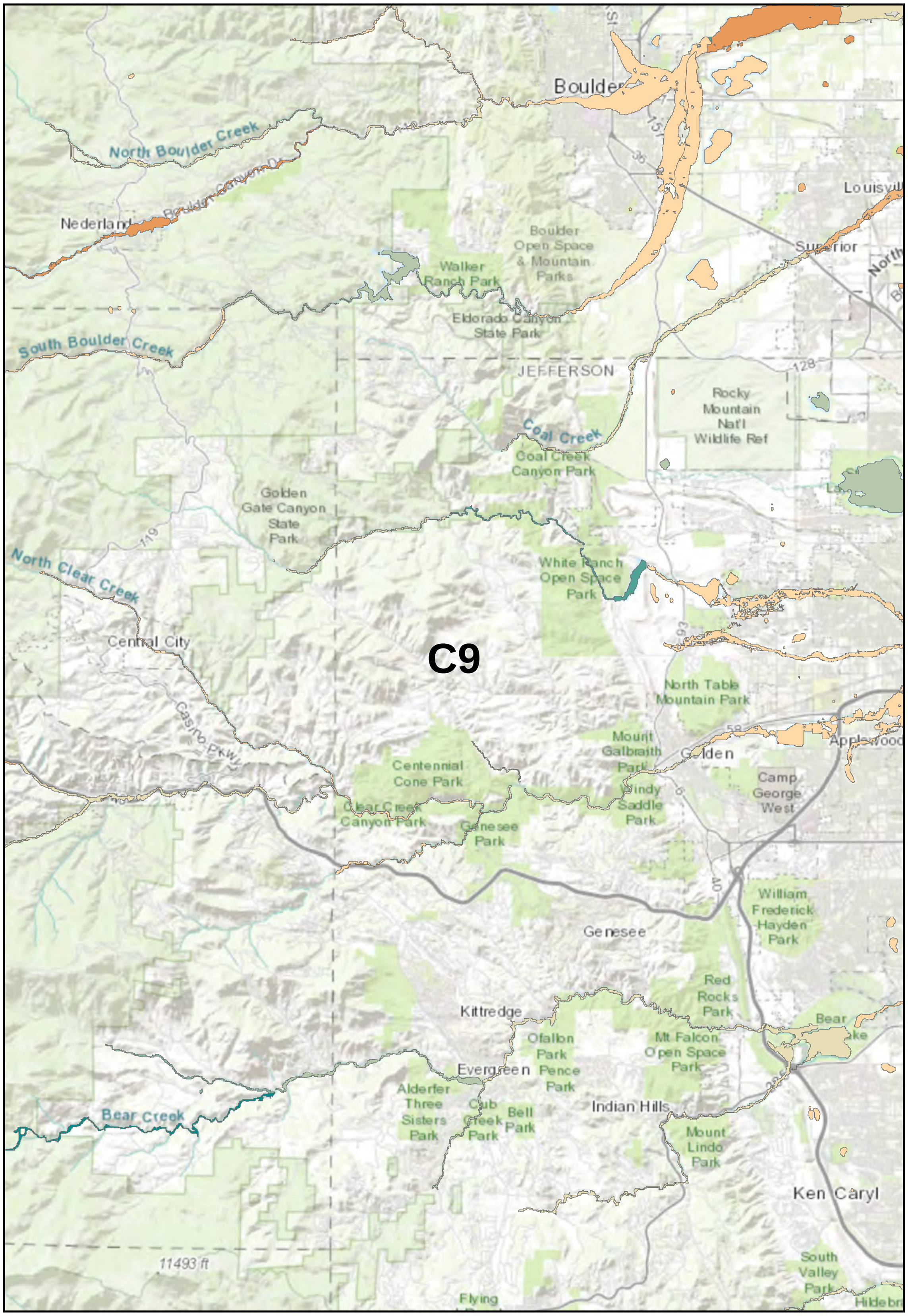

Pole
Creek
Golf Club
BOULDER
James Peak
Wilderness
GILPIN
Arapaho
National
Forest
Vasquez Peak
Wilderness
C8
40
Empire
GRAND
Georgetown
Clear Creek
Loveland
Basin
Ski Area
70
14258 ft
Snake River
Montezuma
CLEAR CREEK
Km
0
2.5
5
10

C9

D8

B9

C8



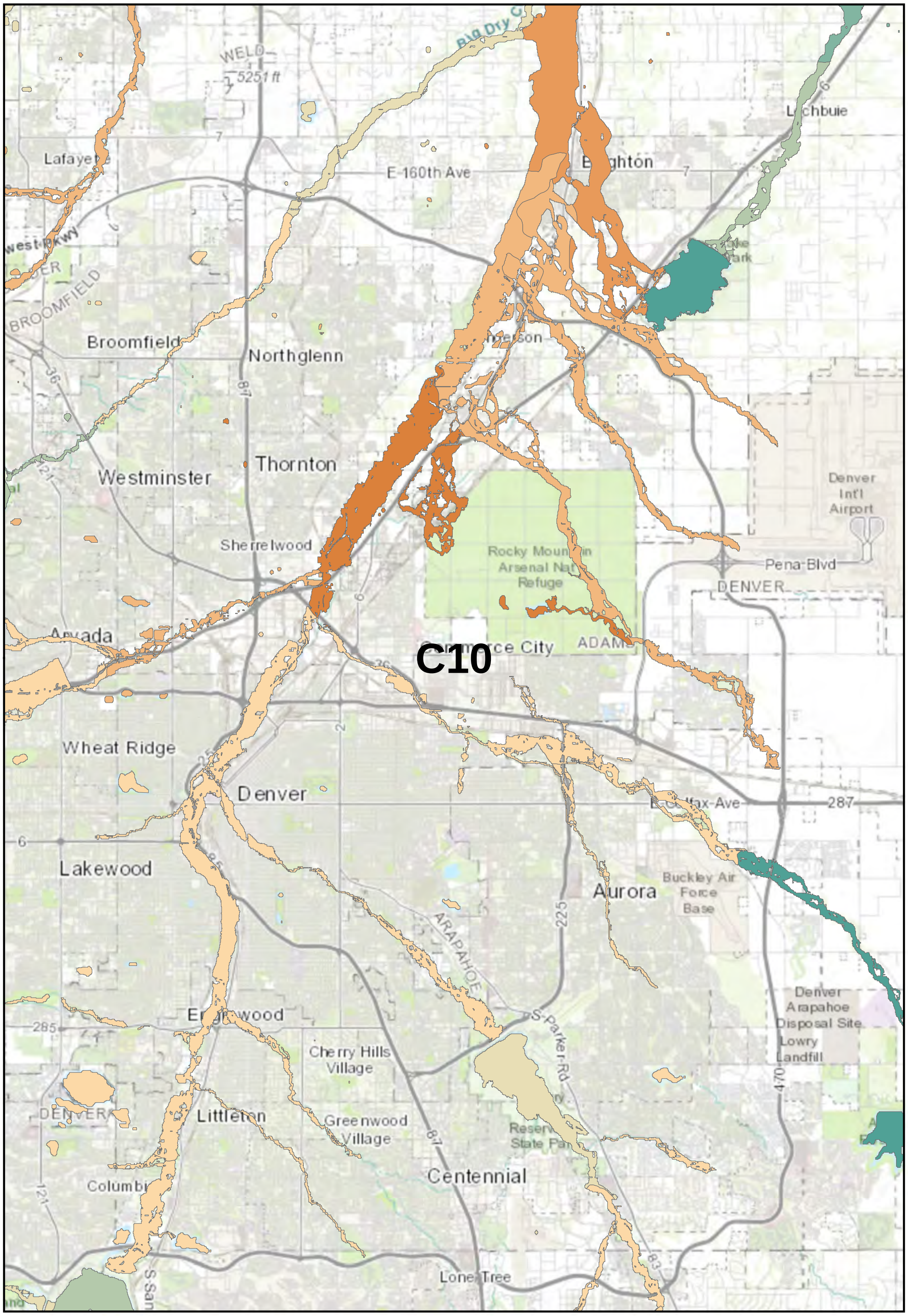
C10

D9

0 2.5 5 10 Km

B10

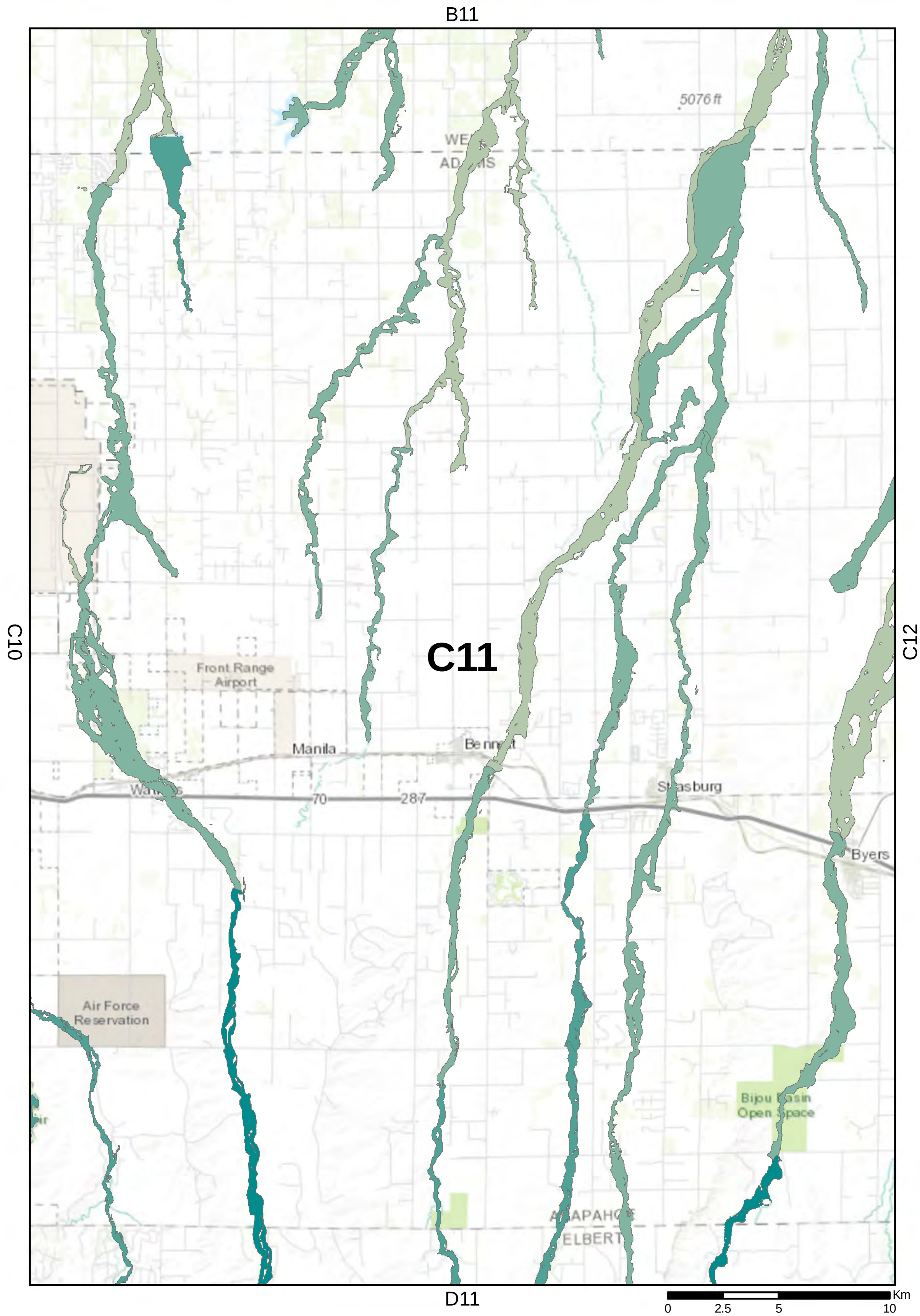
C9



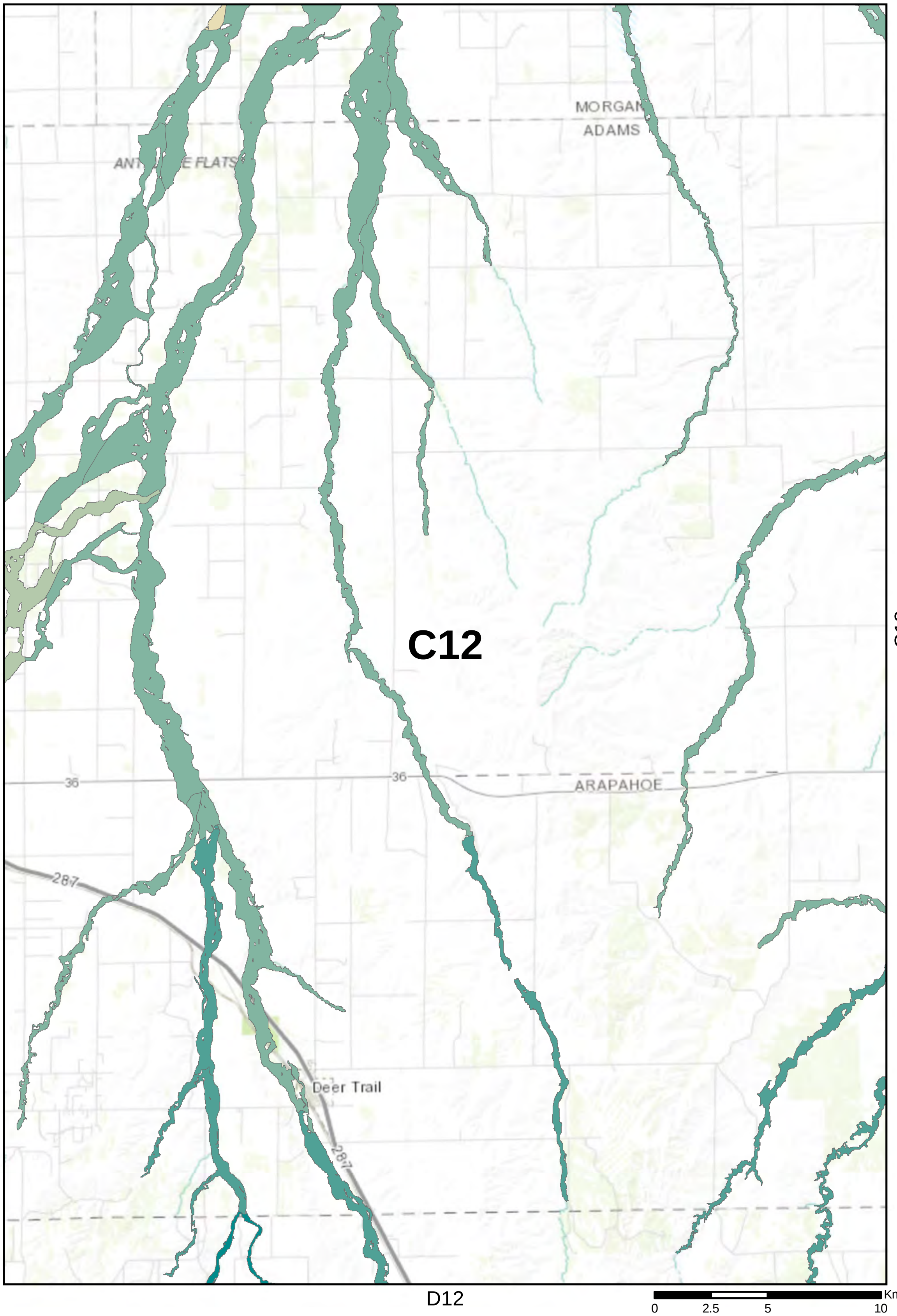
C11

D10

0 2.5 5 10 Km


B11
C10
C11
C12
D11
5076 ft
Front Range Airport
Manila
70
287
Strasburg
Byers
Air Force Reservation
Bijou Basin Open Space
0
2.5
5
10
Km

B12

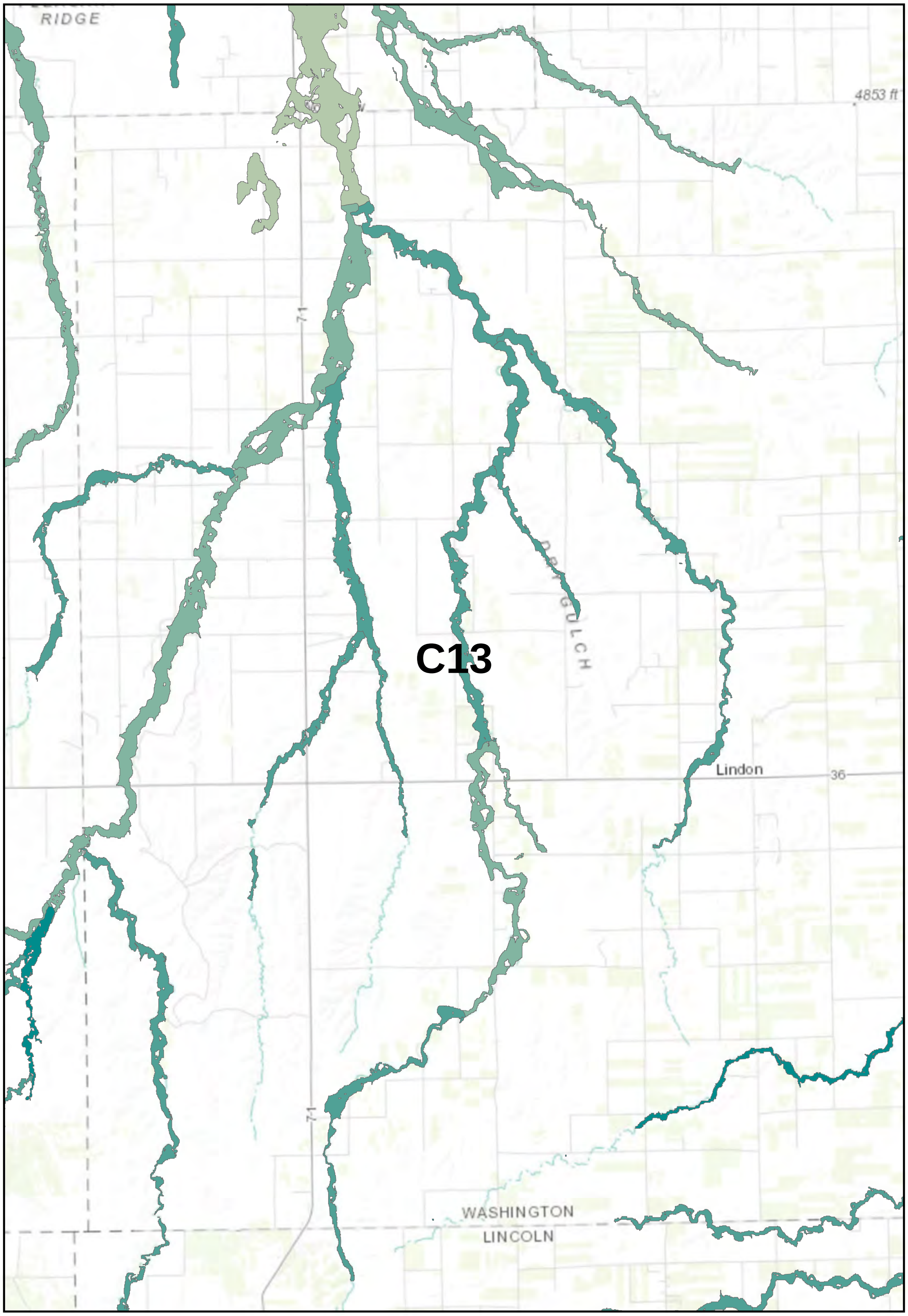


C11

C13

D12

B13

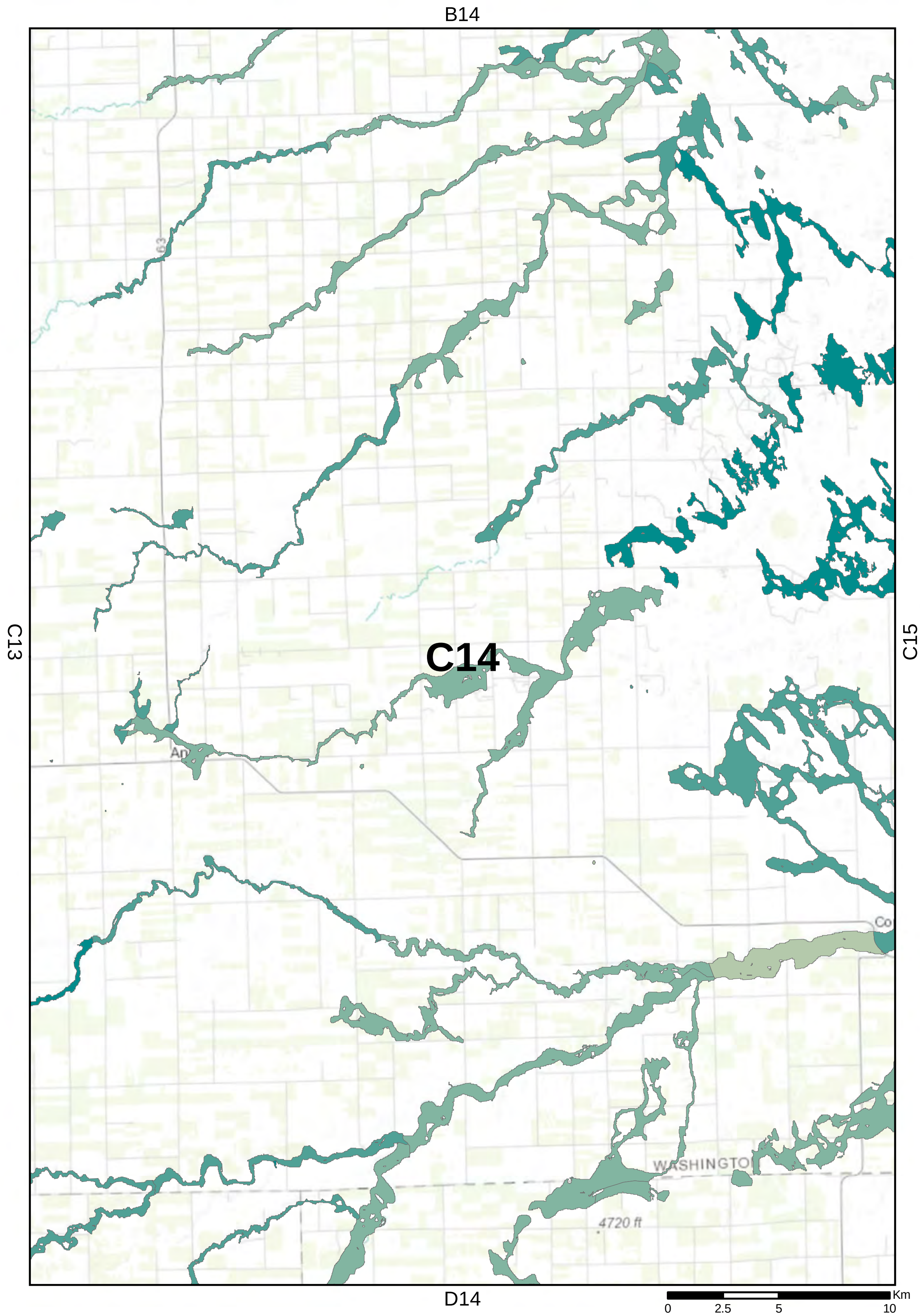


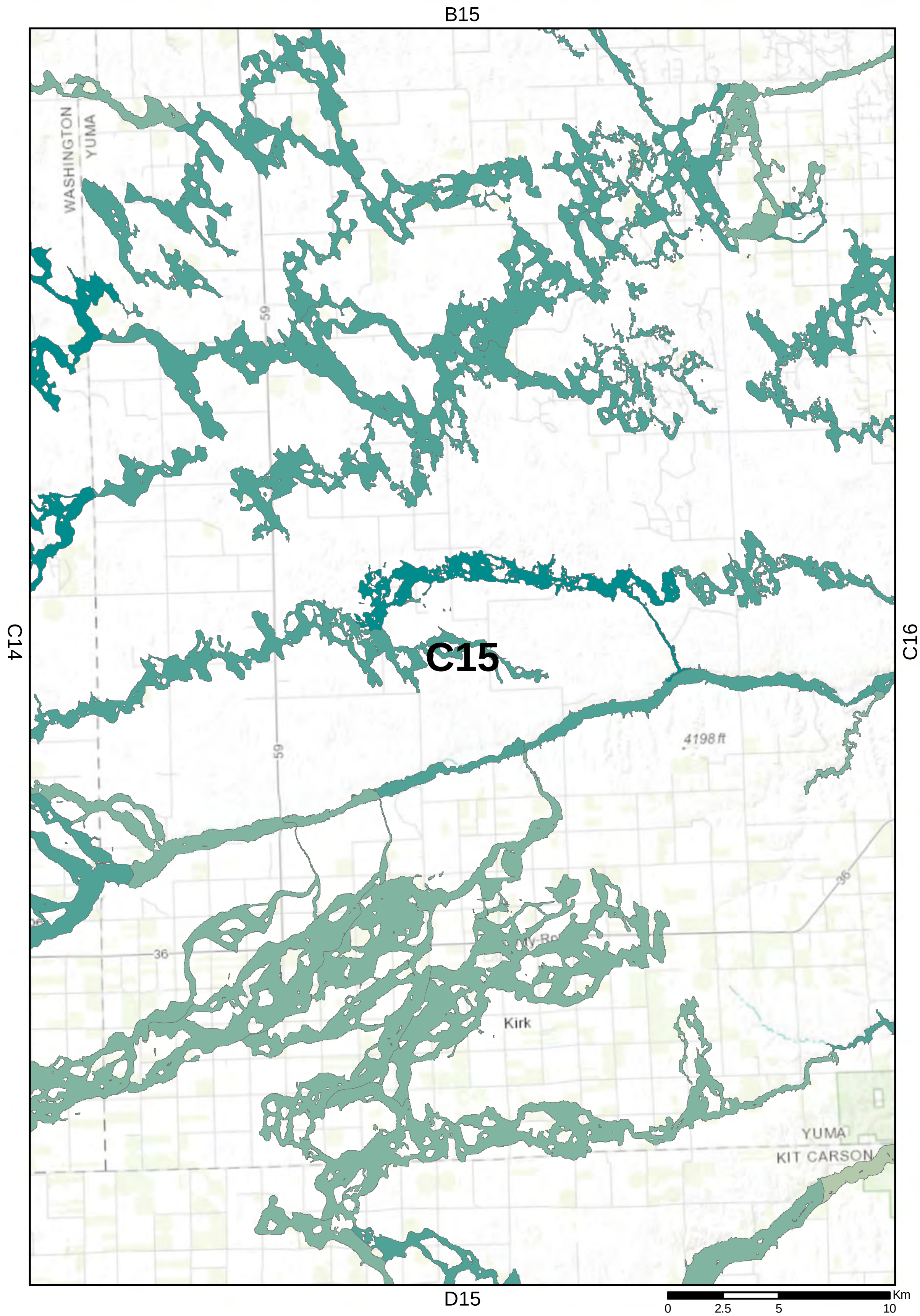
C12

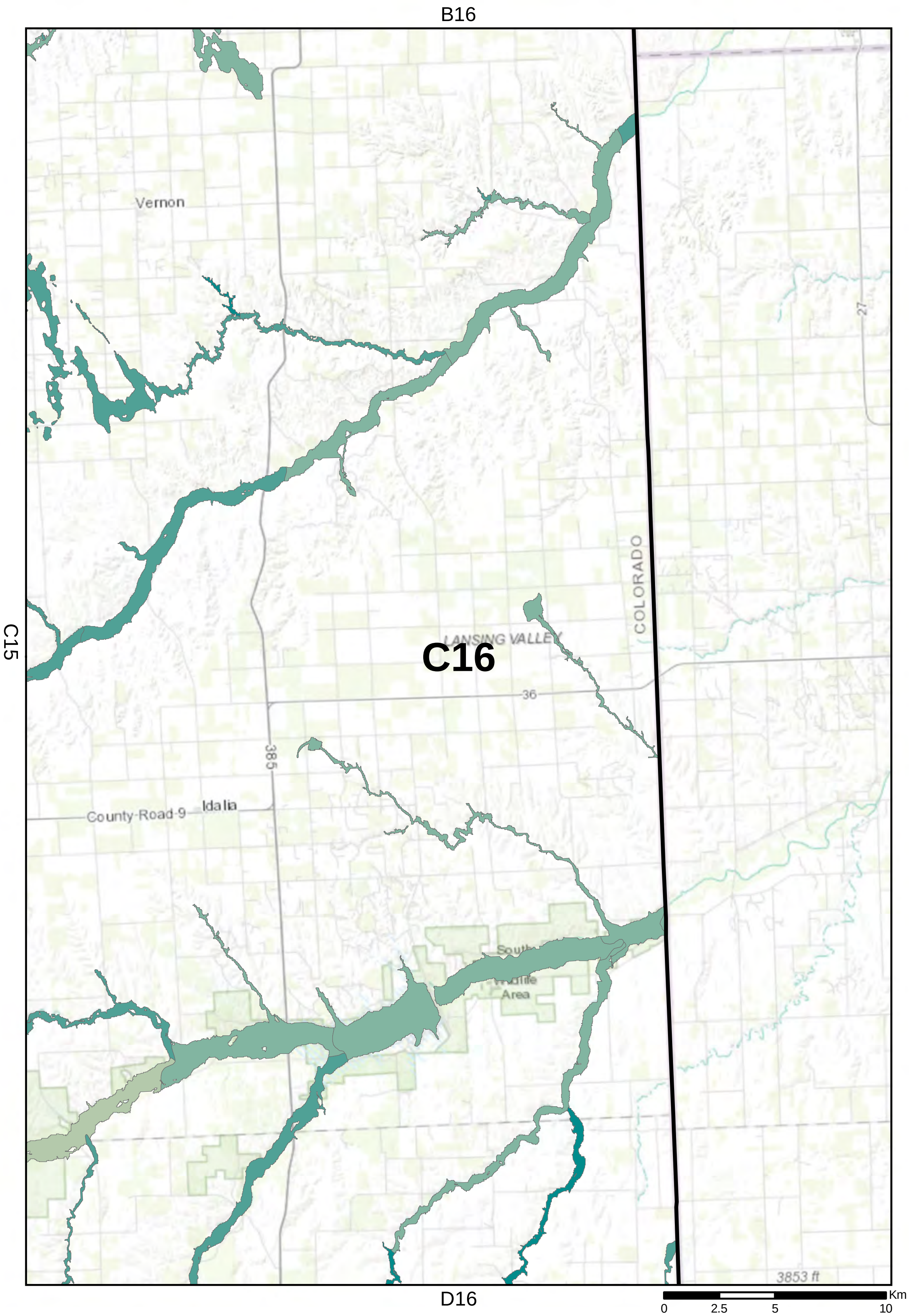
C14

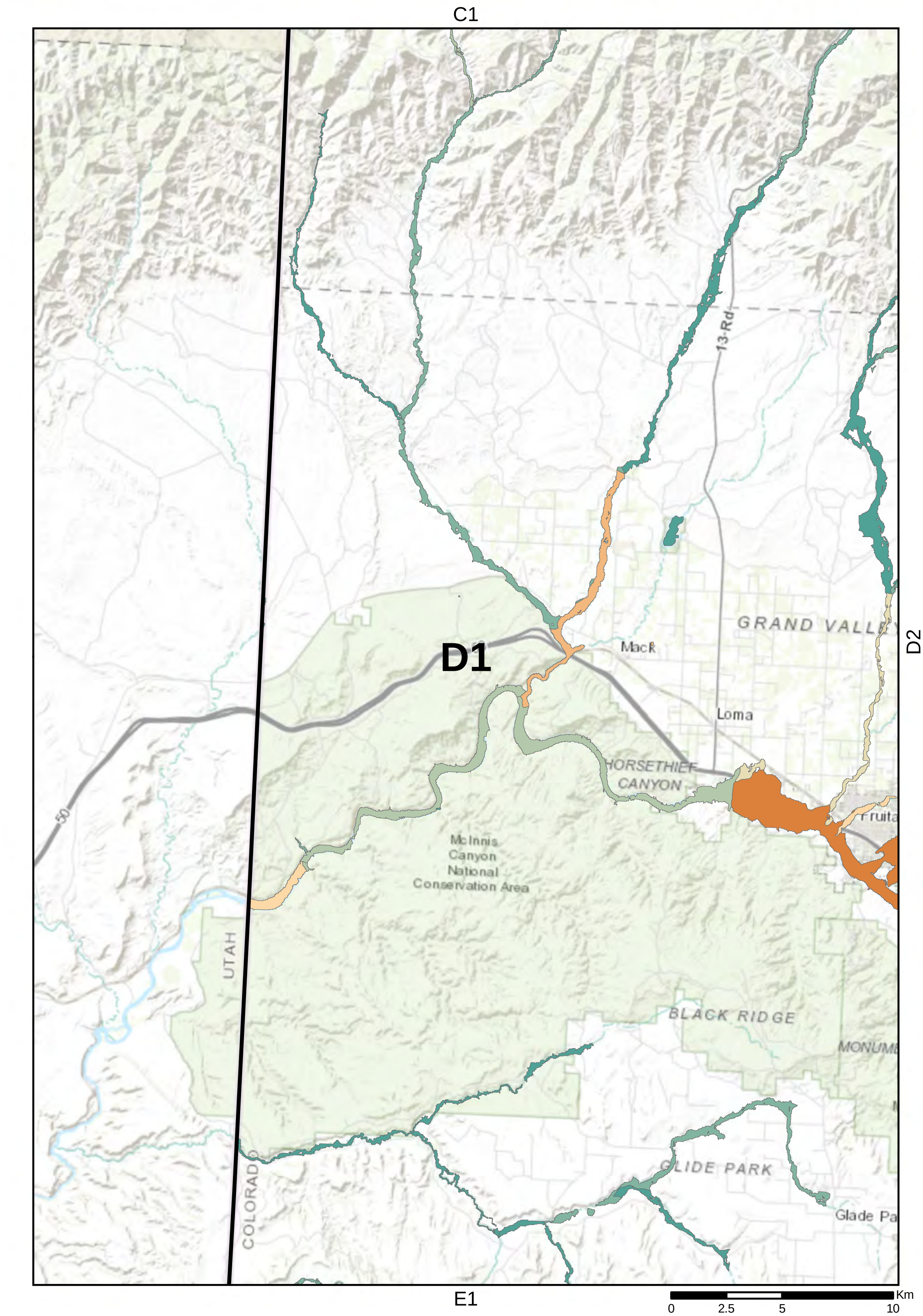
D13

0 2.5 5 10 Km


B14
C13
C14
C15
D14
63
An
Co
WASHINGTO
4720 ft
Km
0
2.5
5
10

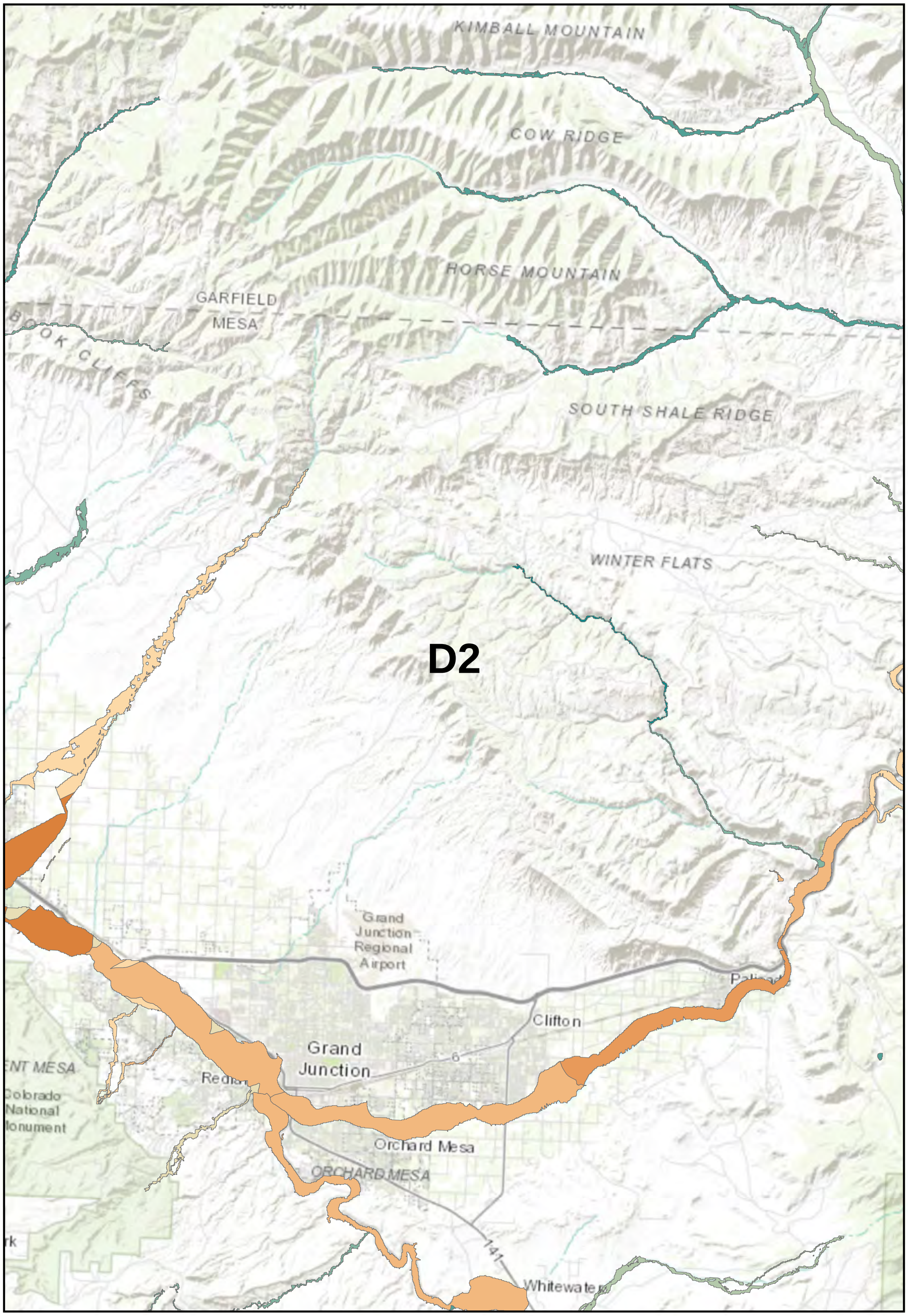

B15
C14
C16
D15
C15
WASHINGTON
YUMA
59
59
4198 ft
36
36
Kirk
YUMA
KIT CARSON
Km
0
2.5
5
10


B16
C15
D16
C16
Vernon
LANSING VALLEY
COLORADO
36
385
27
County Road 9
Idalia
Area
3853 ft
Km
0
2.5
5
10


C1
D1
D2
E1
13 Rd
Mack
Loma
GRAND VALLEY
HORSETHIEF CANYON
Fruita
McInnis Canyon National Conservation Area
50
UTAH
COLORADO
BLACK RIDGE
GLADE PARK
Glade Pa
Km
0
2.5
5
10

C2

D1



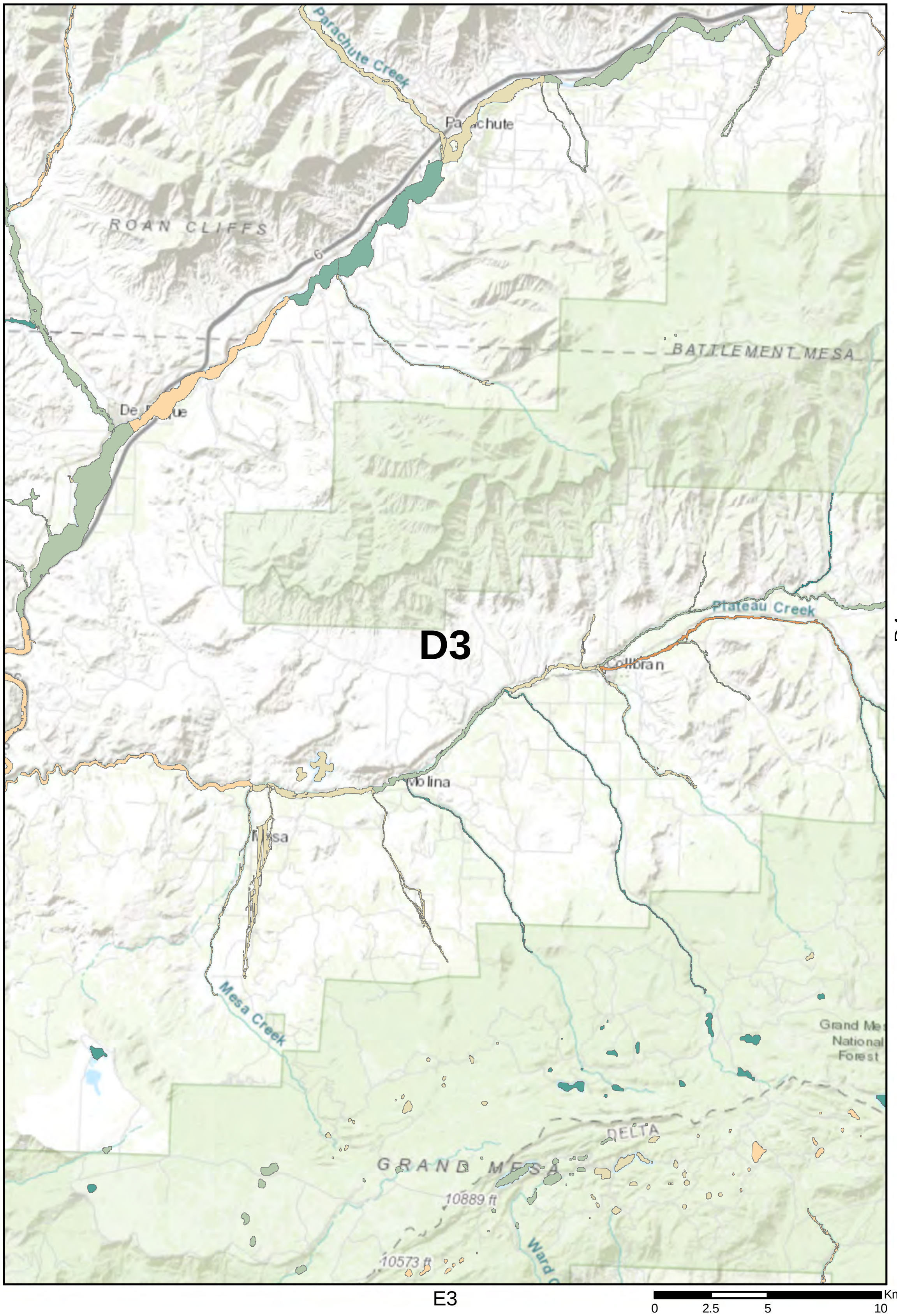
D3

E2

0 2.5 5 10 Km

C3

D2

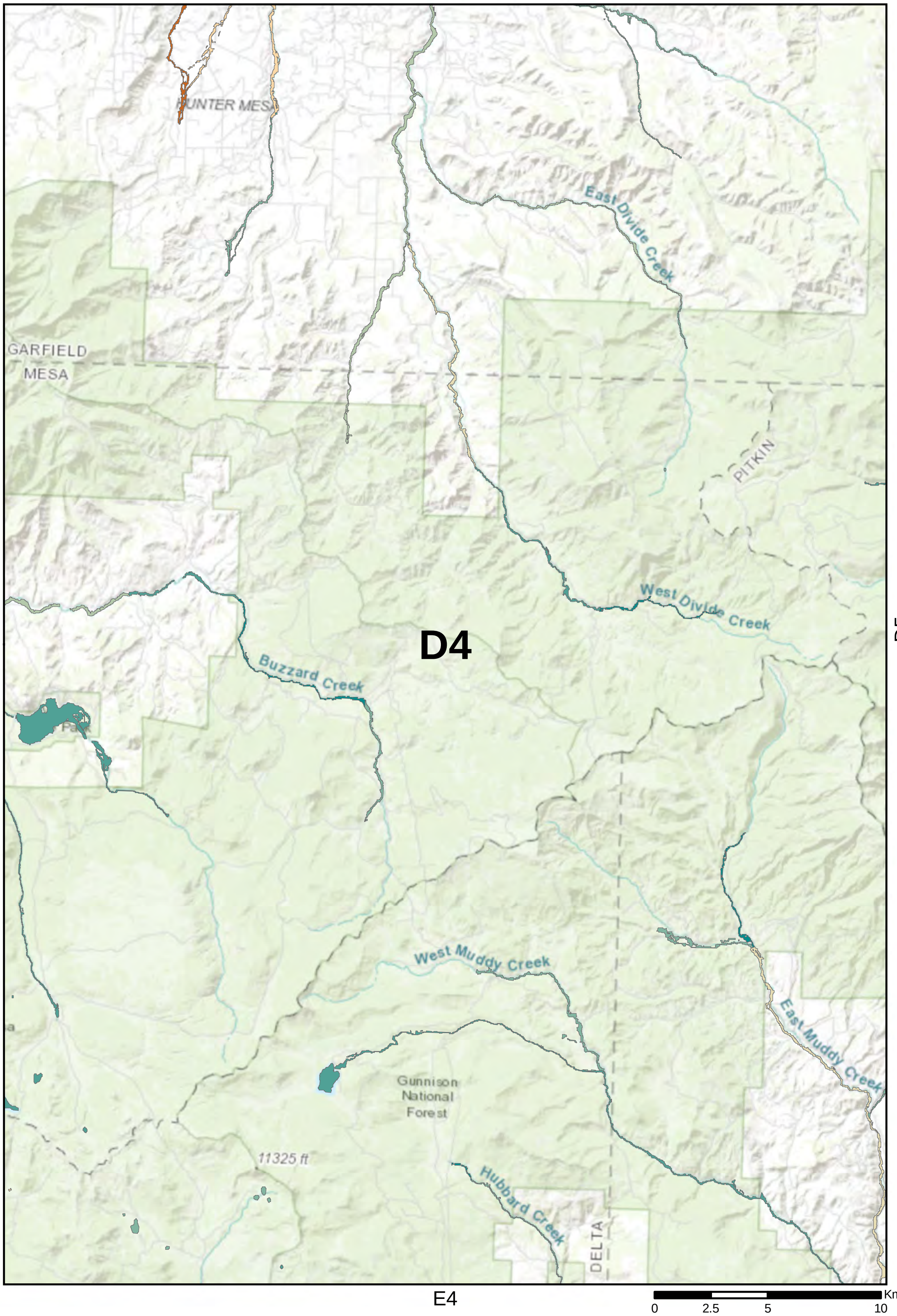

Parachute Creek
Parachute
ROAN CLIFFS
6
BATTLEMENT MESA
Plateau Creek
D3
Collbran
Molina
Mesa
Mesa Creek
Grand Mesa
National
Forest
DELTA
GRAND MESA
10889 ft
10573 ft
Ward C
Km
0
2.5
5
10

D4

E3

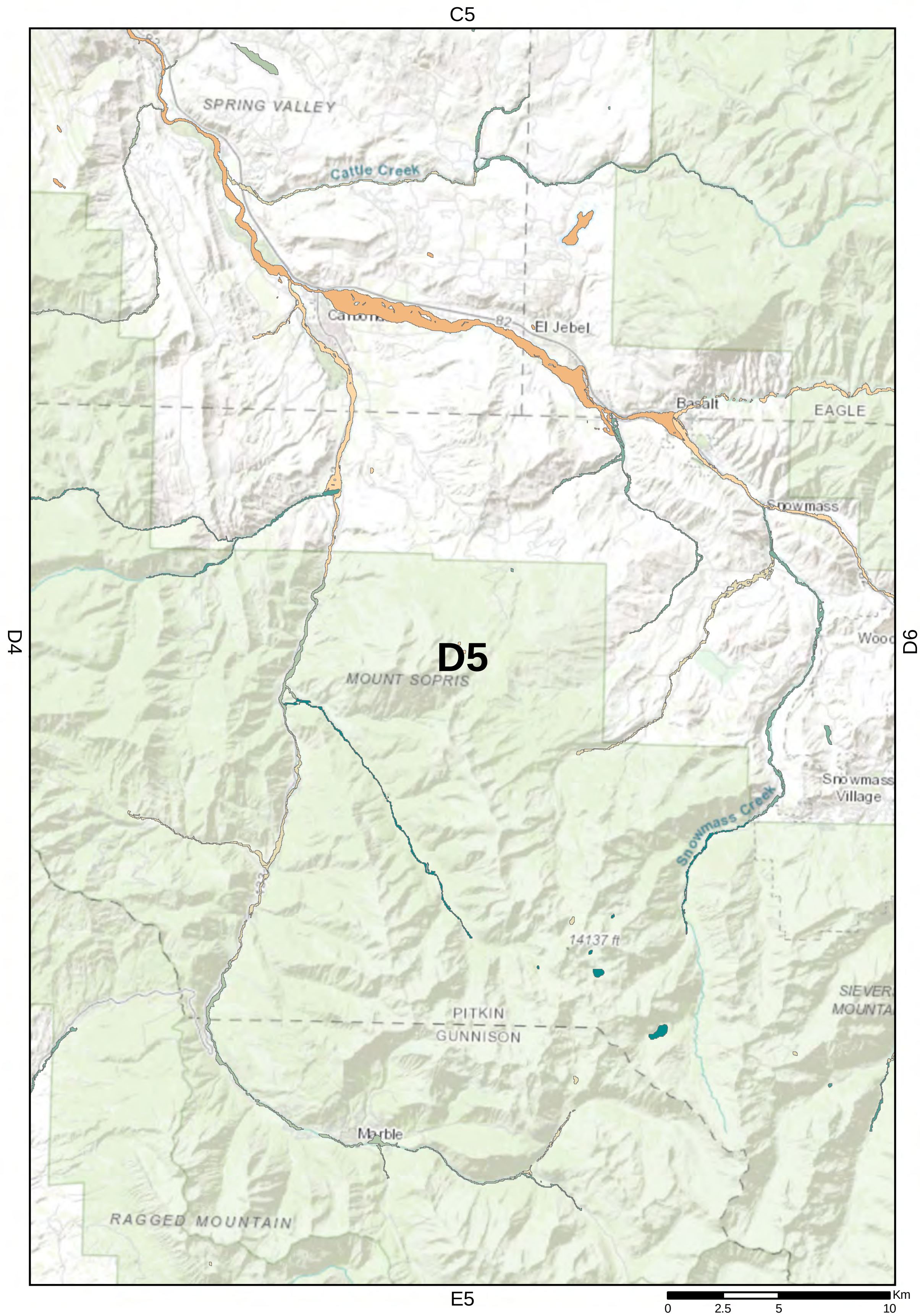
C4

D3


HUNTER MESA
GARFIELD
MESA
East Divide Creek
PITKIN
West Divide Creek
D4
Buzzard Creek
West Muddy Creek
East Muddy Creek
Gunnison
National
Forest
11325 ft
Hubbard Creek
DELTA
0
2.5
5
10
Km

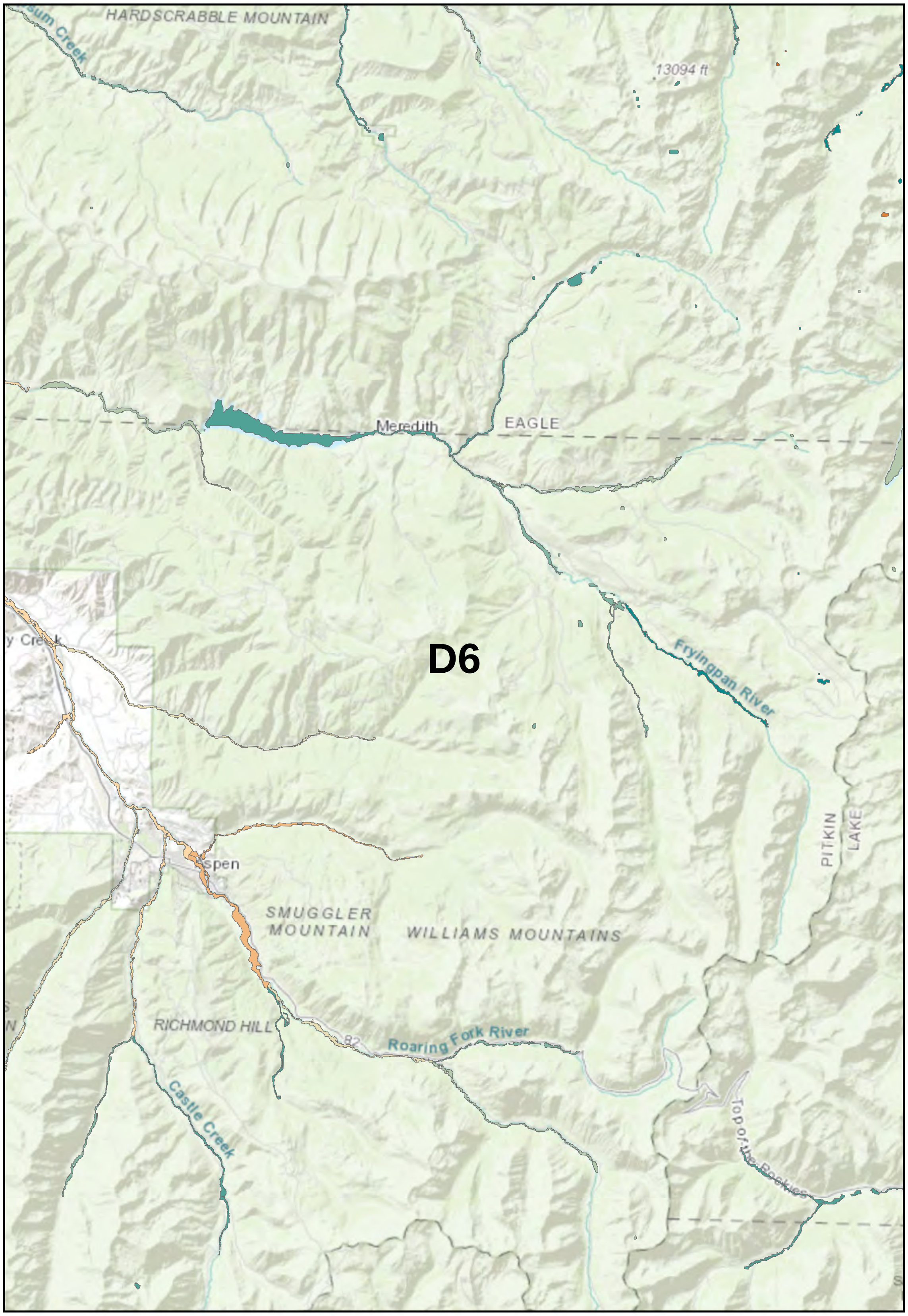
D5

E4


C5
D4
D6
E5
D5
SPRING VALLEY
Cattle Creek
El Jebel
82
Basalt
EAGLE
Snowmass
MOUNT SOPRIS
Snowmass Creek
Snowmass Village
14137 ft
PITKIN
GUNNISON
Marble
RAGGED MOUNTAIN
Km
0
2.5
5
10

C6

D5



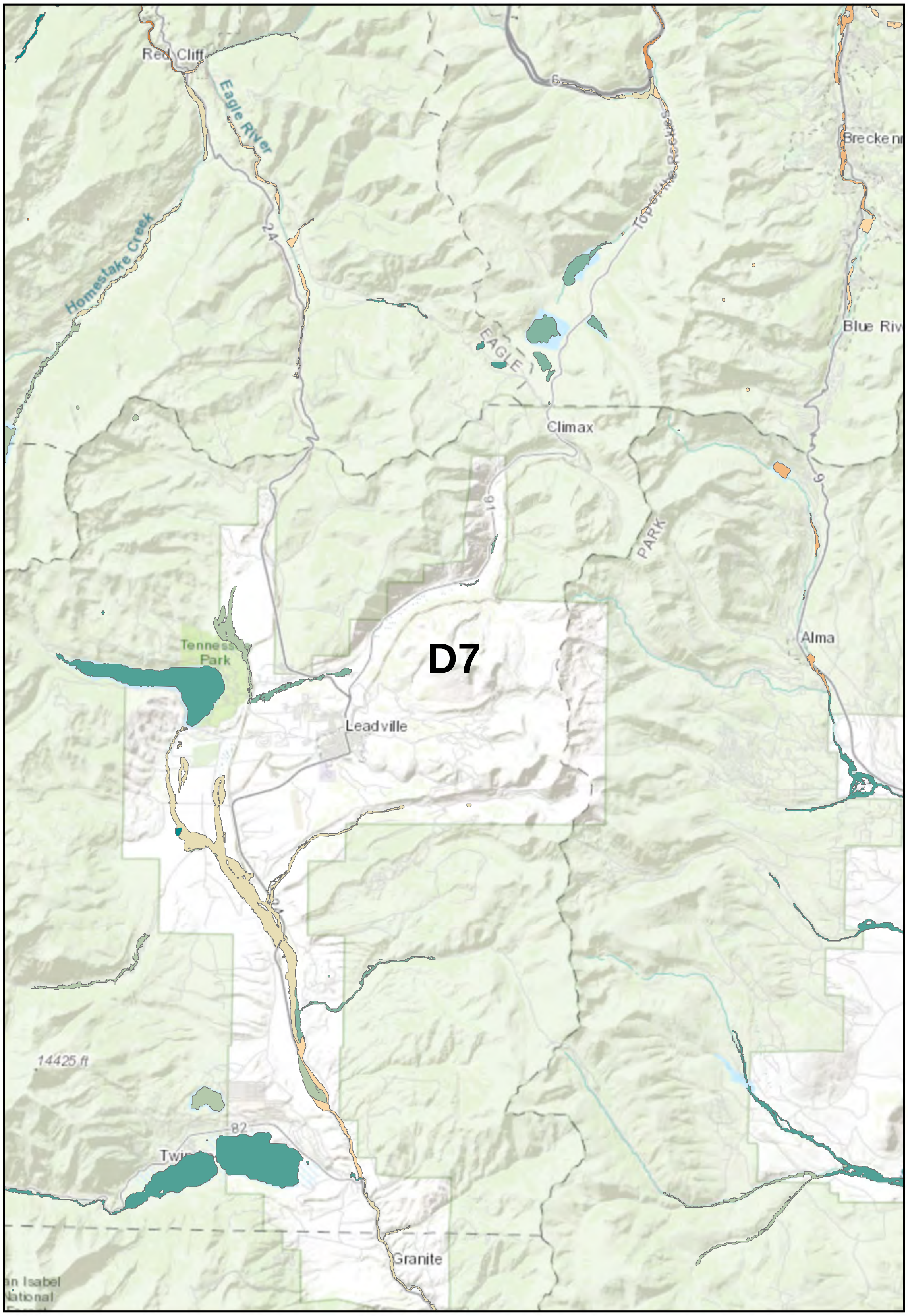
D7

E6

0 2.5 5 10 Km

C7

D6

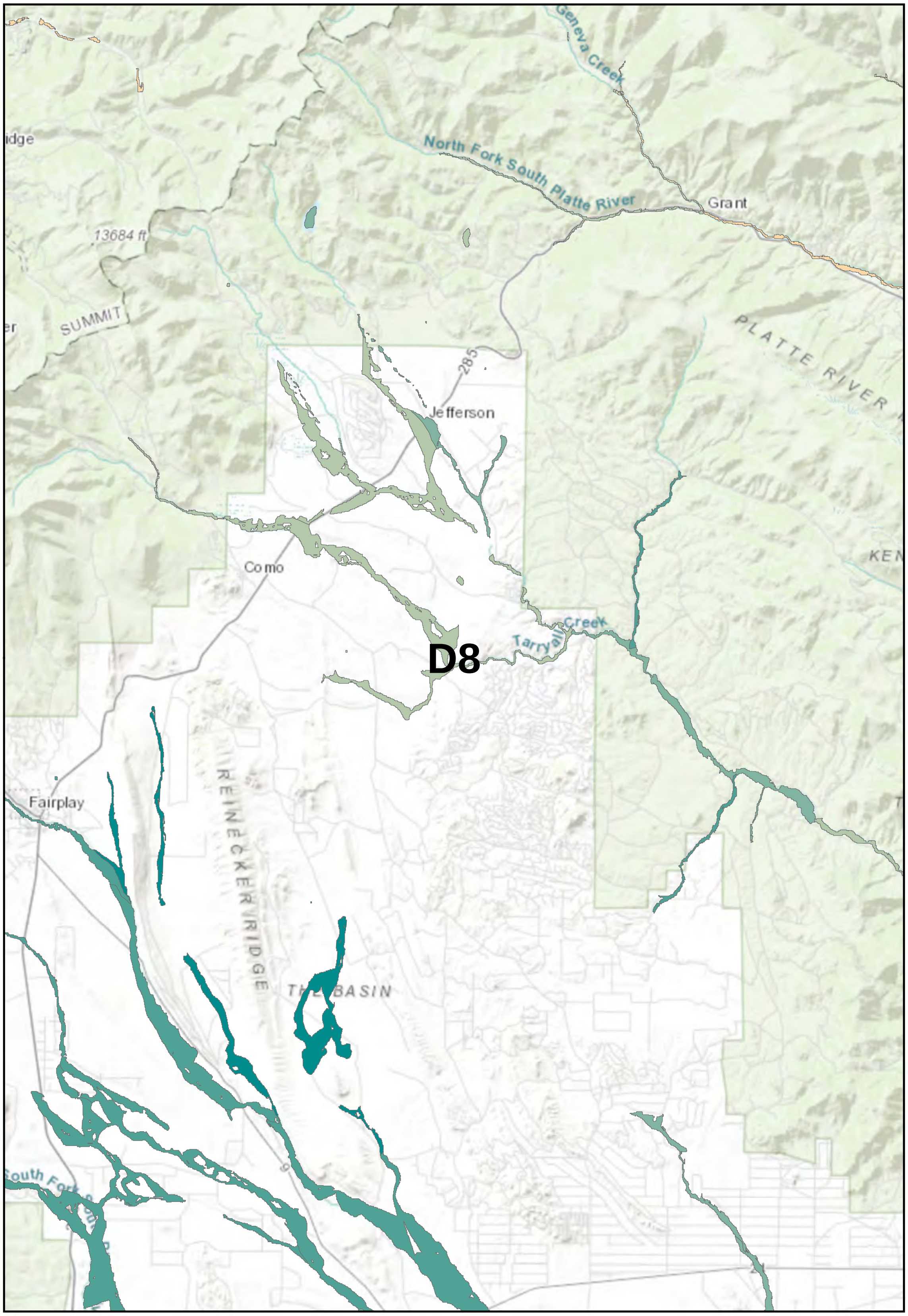


D8

E7

0 2.5 5 10 Km

C8

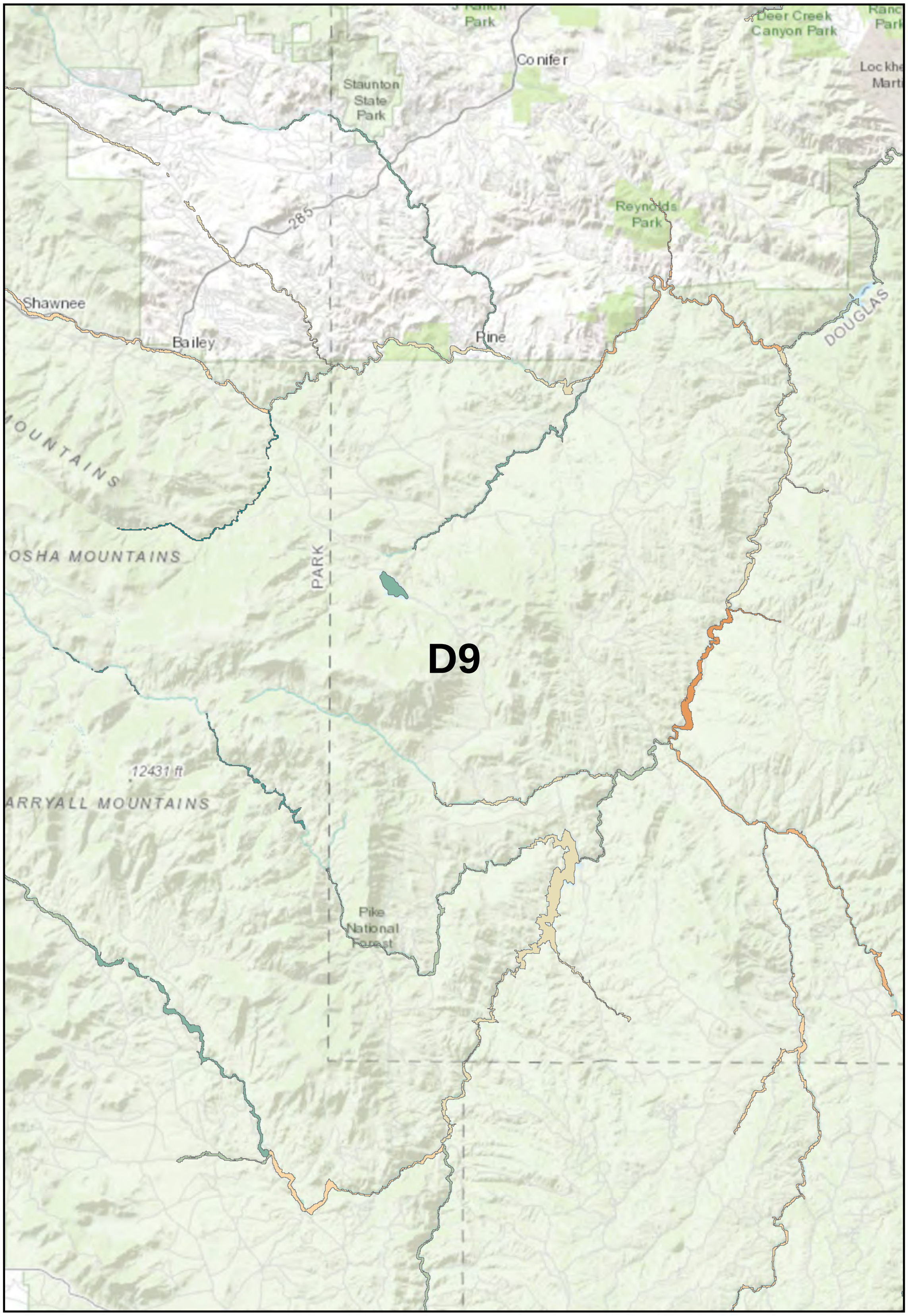

Geneva Creek
North Fork South Platte River
Grant
13684 ft
SUMMIT
PLATTE RIVER
285
Jefferson
Como
Tarryall Creek
D8
REINECKER RIDGE
THE BASIN
Fairplay
South Fork
9
Km
0
2.5
5
10

D7

D9

E8

C9



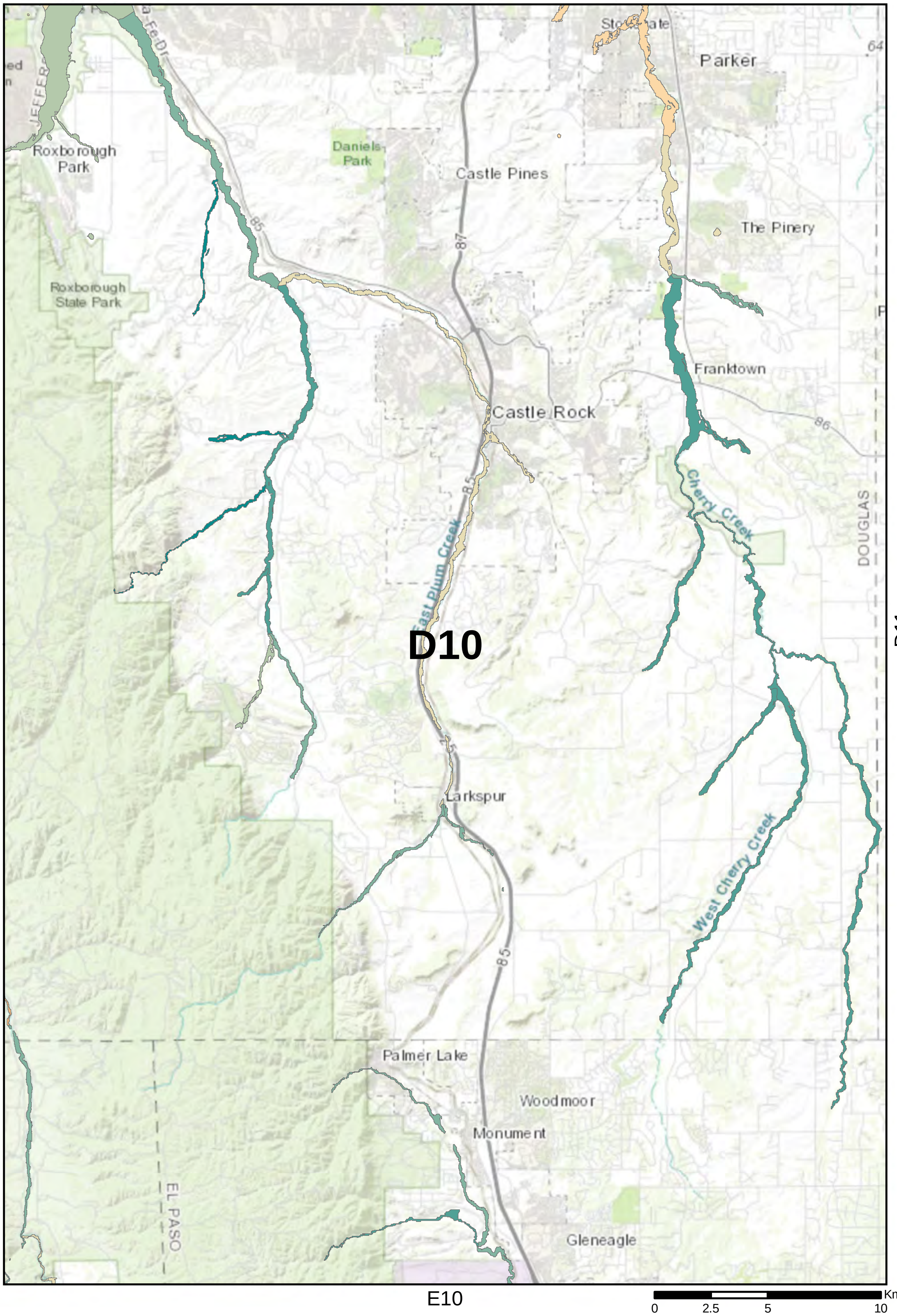
D8

D10

E9

0 2.5 5 10 Km

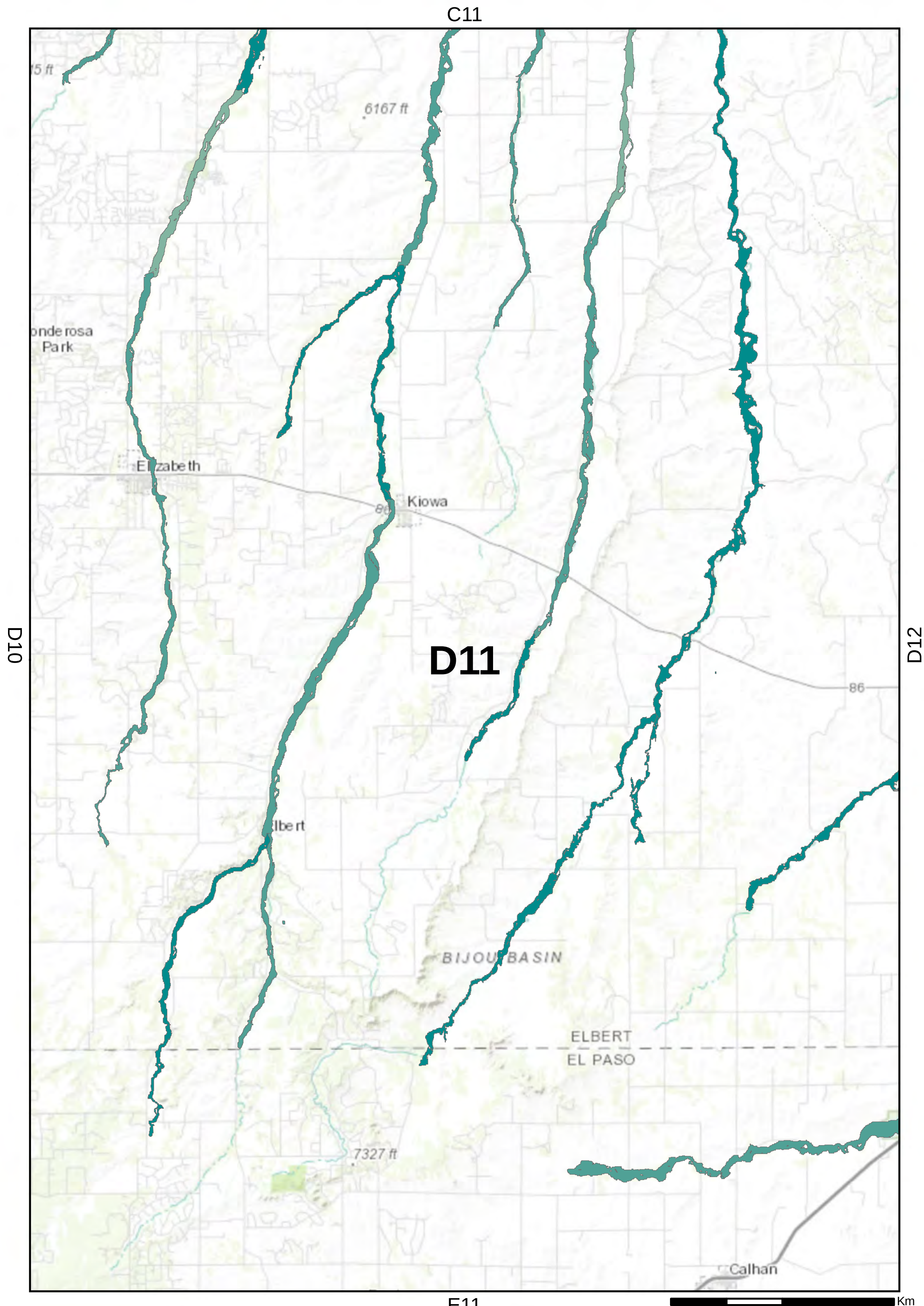
C10



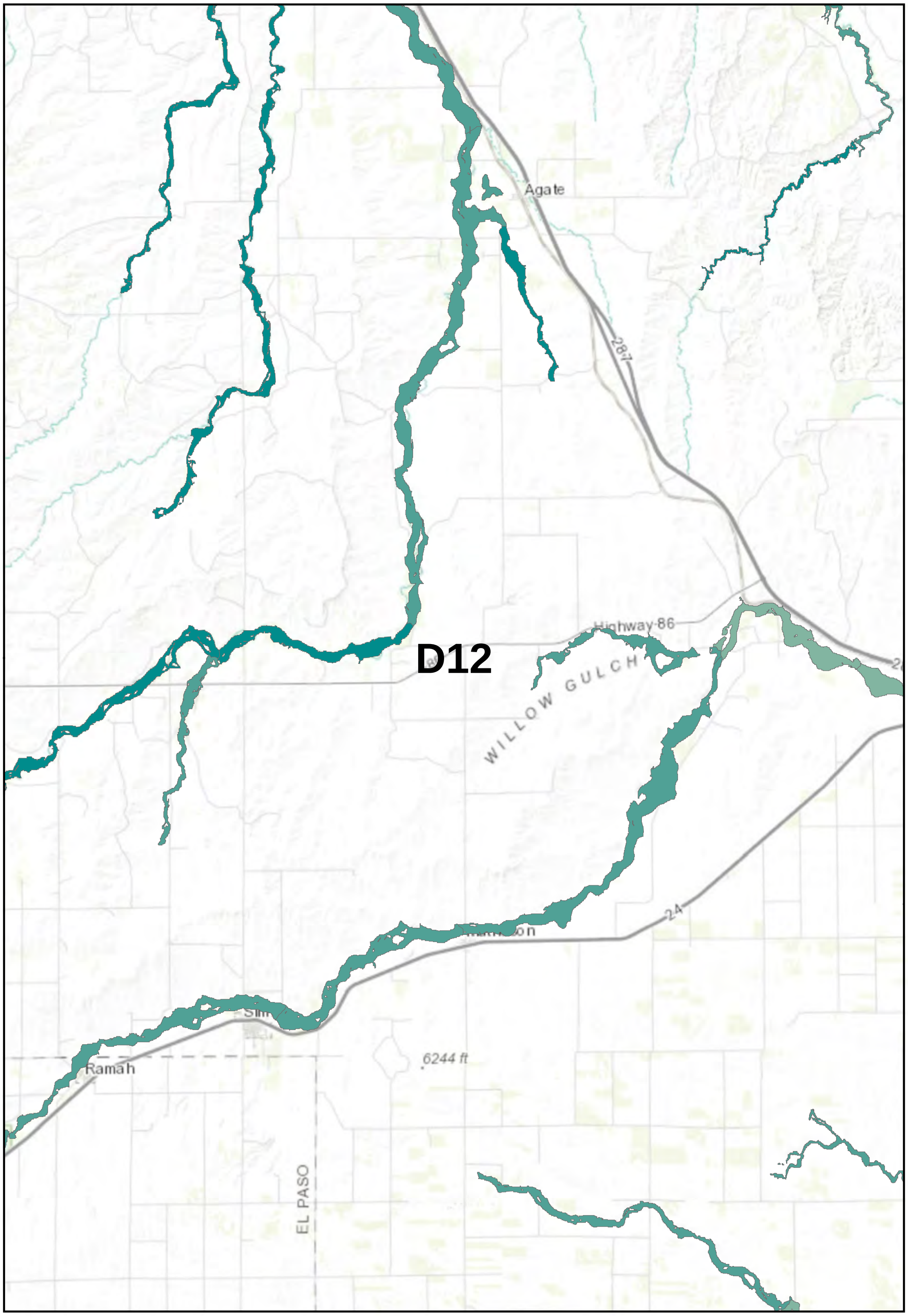
D9

D11

E10


C11
D10
D12
E11
D11
6167 ft
onderosa
Park
Elizabeth
Kiowa
86
lbert
BIJOU BASIN
ELBERT
EL PASO
7327 ft
Calhan
Km
0
2.5
5
10

C12



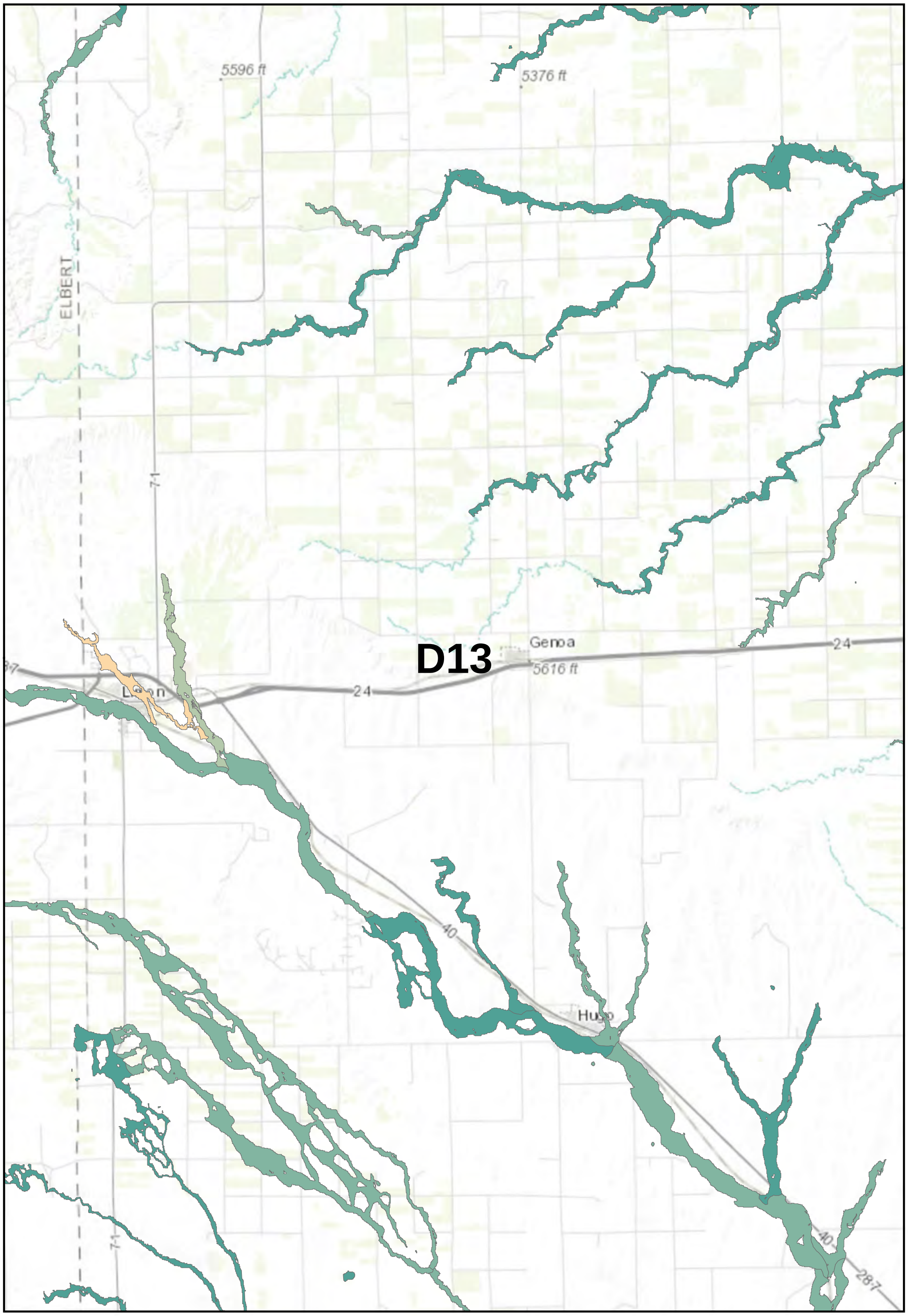
D11

D13

E12

0 2.5 5 10 Km

C13

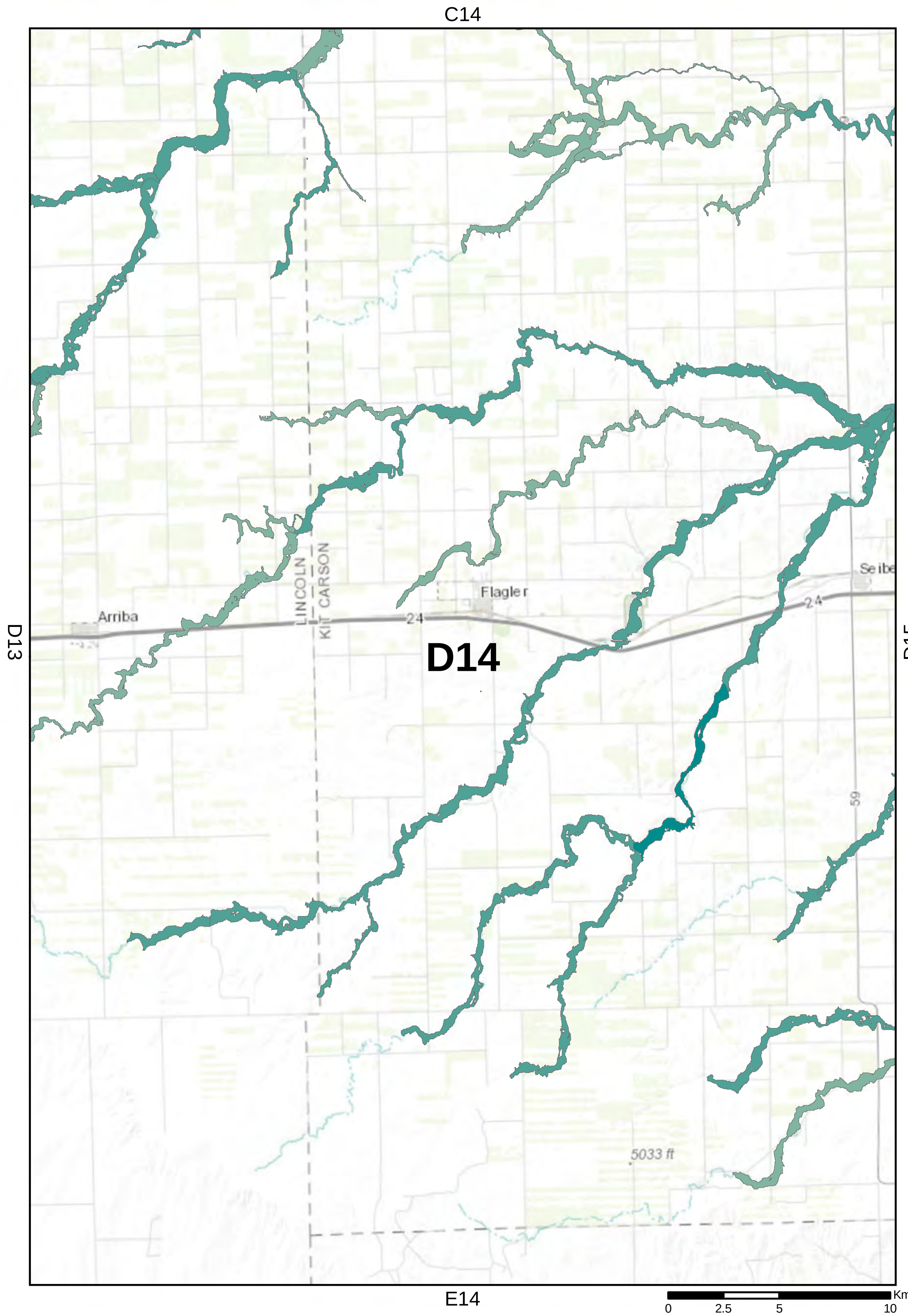


D12

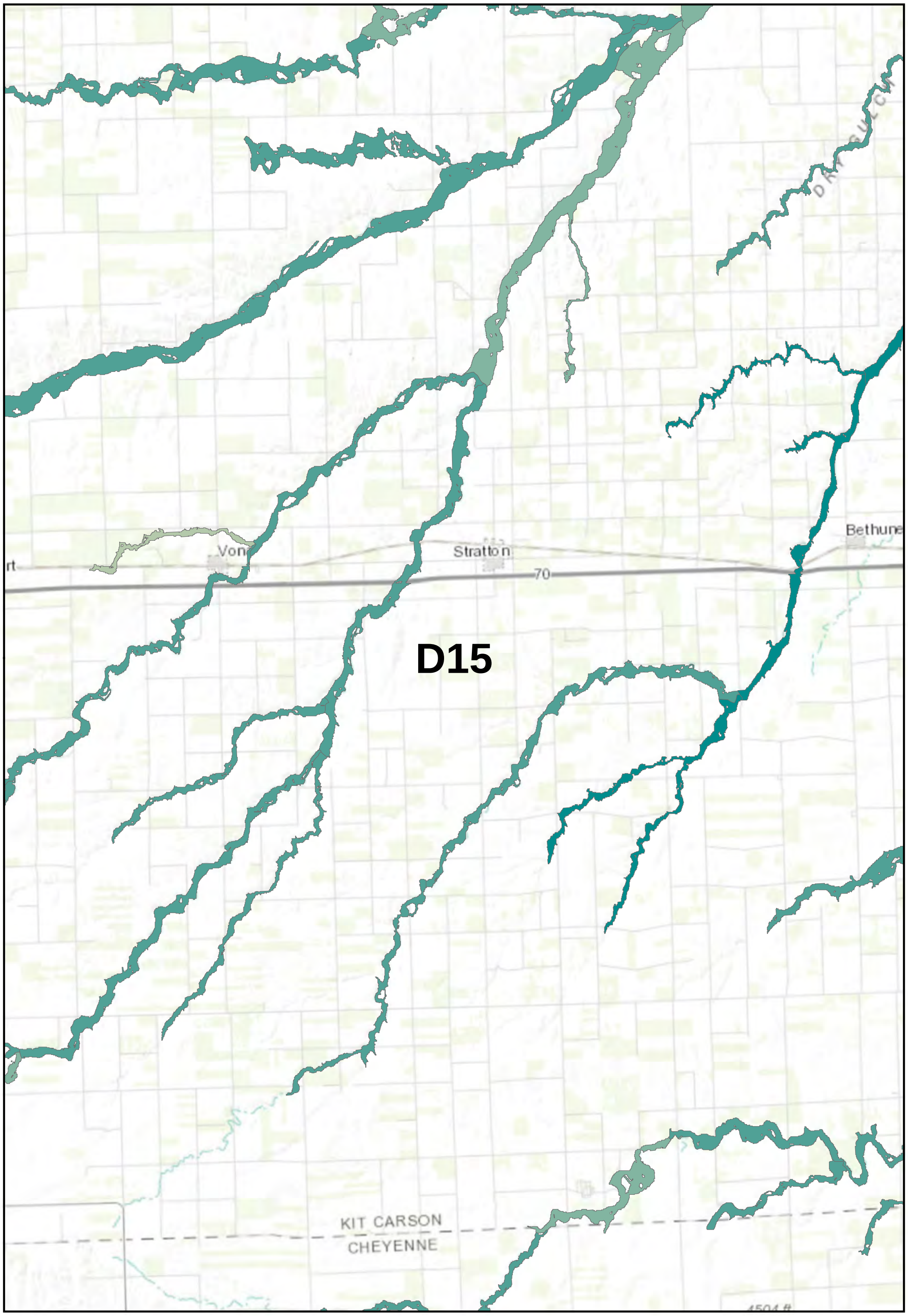
D14

E13

0 2.5 5 10 Km


C14
D13
D15
E14
D14
Arriba
Flagler
LINCOLN
KIT CARSON
24
59
5033 ft
Km
0
2.5
5
10

C15



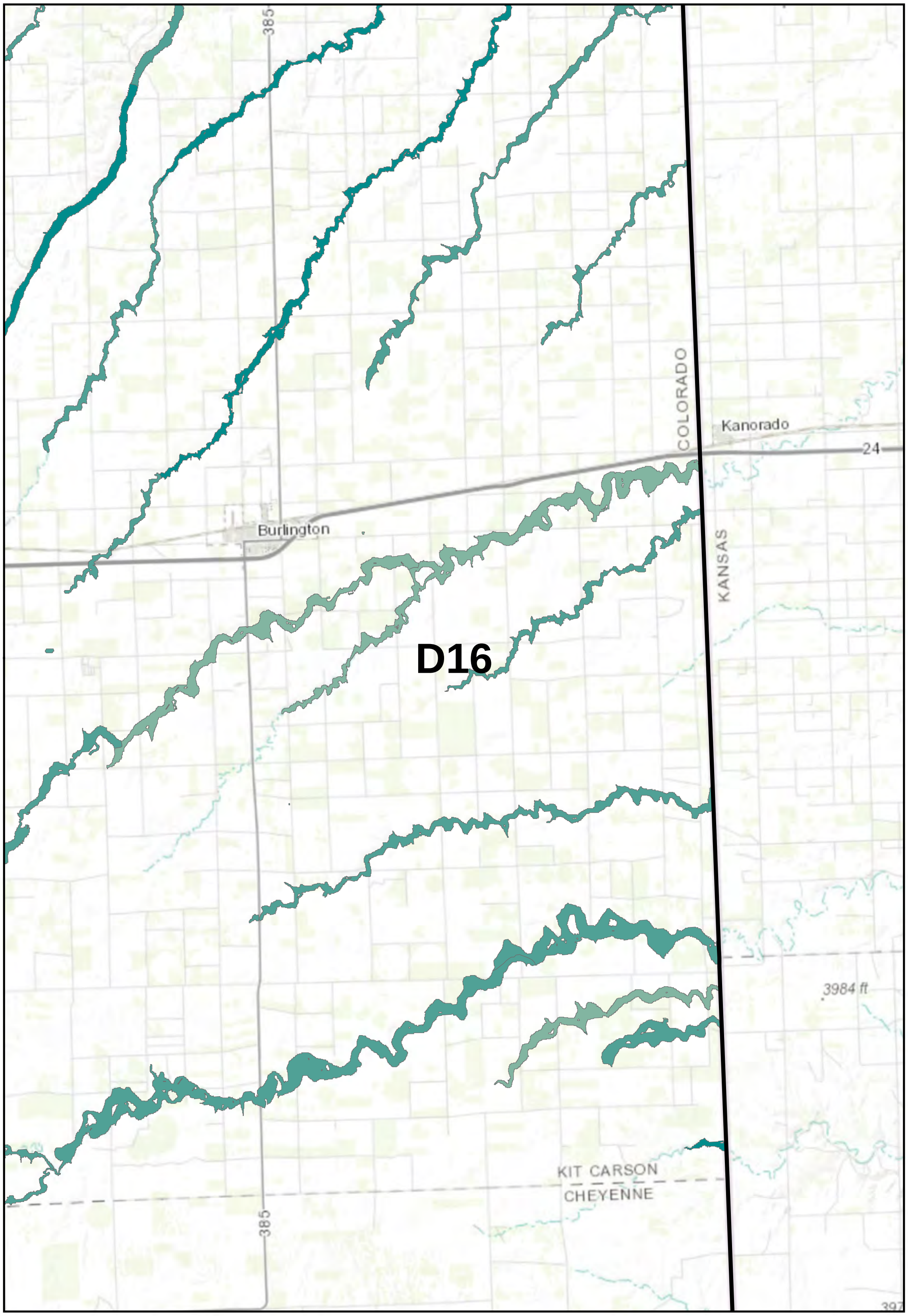
D14

D16

E15

0 2.5 5 10 Km

C16

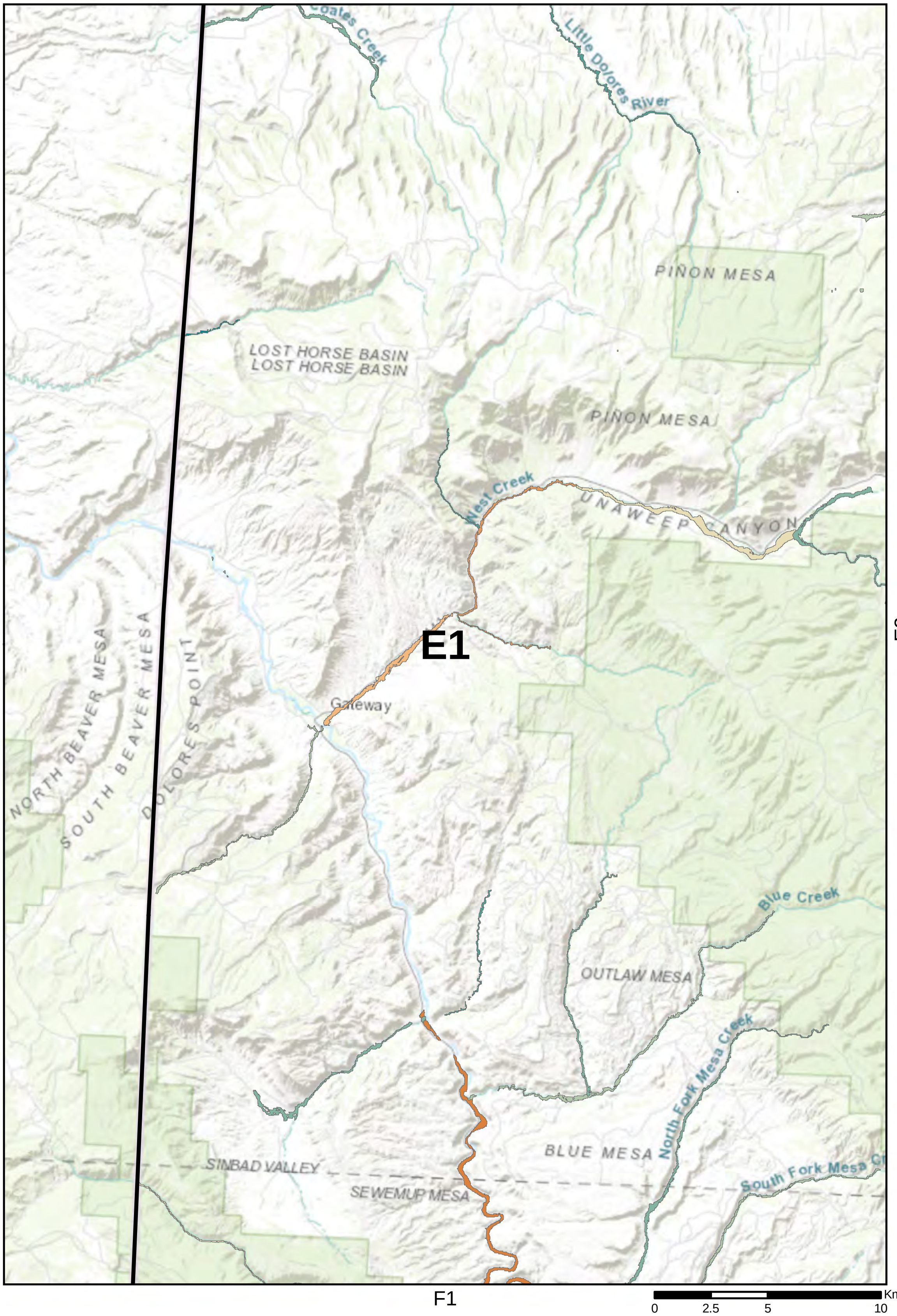


D15

E16

0 2.5 5 10 Km

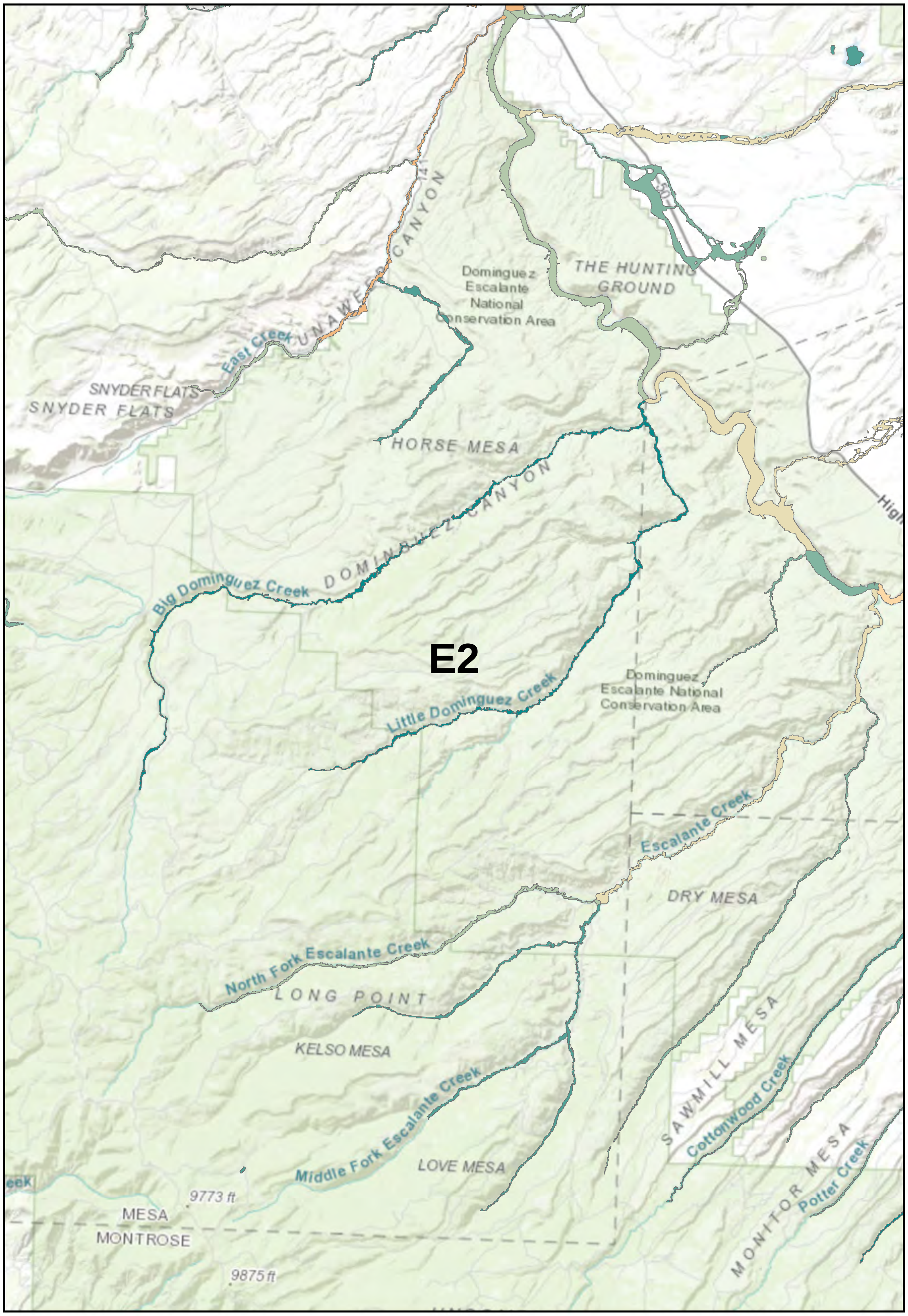
D1


Coates Creek
Little Dolores River
PIÑON MESA
LOST HORSE BASIN
LOST HORSE BASIN
PIÑON MESA
West Creek
UNAWEEP CANYON
E1
Gateway
NORTH BEAVER MESA
SOUTH BEAVER MESA
DOLORES POINT
Blue Creek
OUTLAW MESA
North Fork Mesa Creek
BLUE MESA
SINBAD VALLEY
SEWEMUP MESA
South Fork Mesa Cr
Km
0
2.5
5
10

E2

F1

D2


E2
Dominguez Escalante National Conservation Area
THE HUNTING GROUND
UNAWEEP CANYON
East Creek
SNYDER FLATS
SNYDER FLATS
HORSE MESA
DOMINGUEZ CANYON
Big Dominguez Creek
Little Dominguez Creek
Dominguez Escalante National Conservation Area
Escalante Creek
DRY MESA
North Fork Escalante Creek
LONG POINT
KELSO MESA
Middle Fork Escalante Creek
LOVE MESA
SAWMILL MESA
Cottonwood Creek
MONITOR MESA
Potter Creek
9773 ft
MESA
MONTROSE
9875 ft
0 2.5 5 10 Km

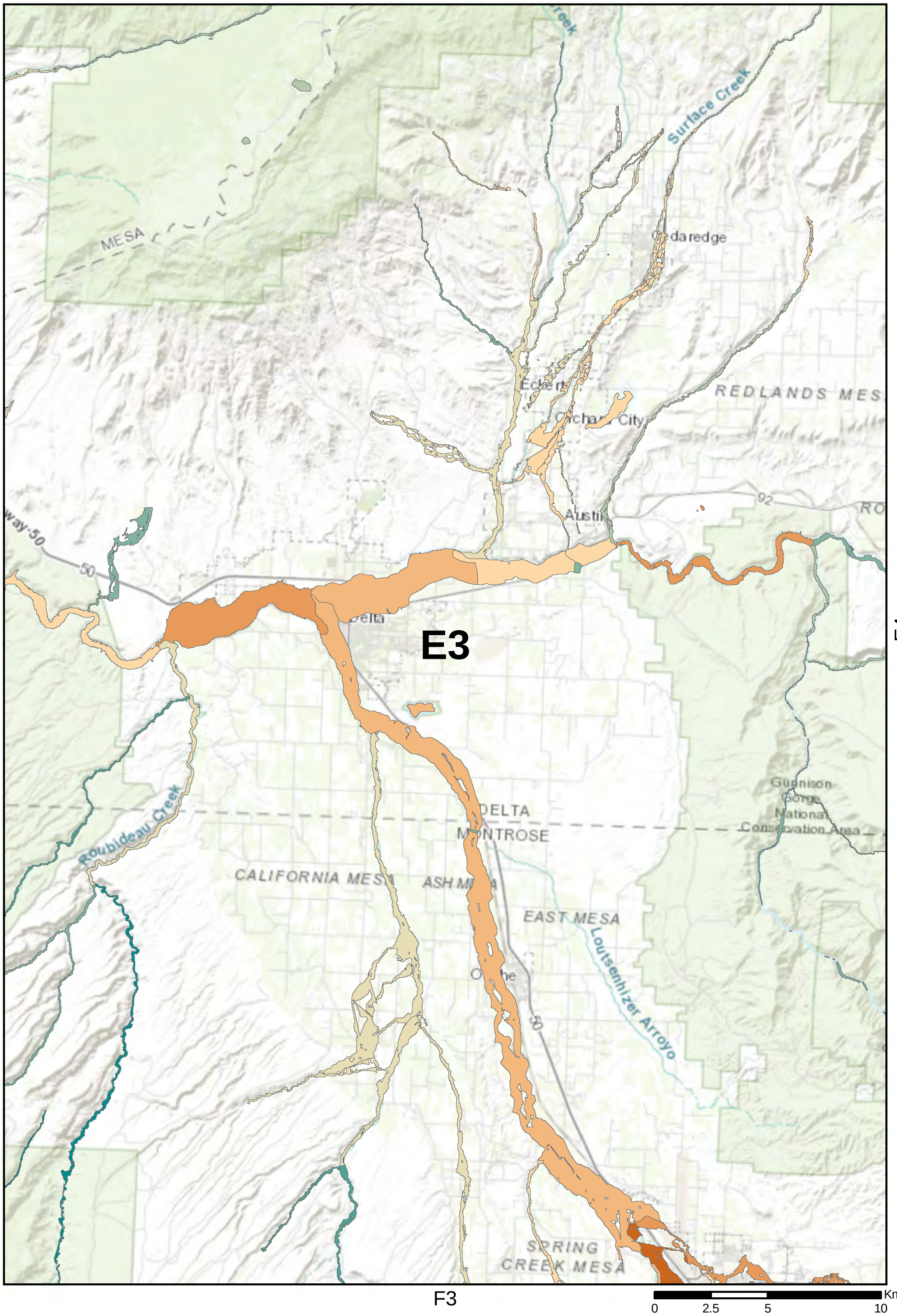
E1

E3

F2

D3

E2


MESA
Surface Creek
Cedaredge
Eckert
Orchard City
REDLANDS MESA
Austin
92
Delta
E3
50
Roubideau Creek
DELTA
MONTROSE
CALIFORNIA MESA
EAST MESA
Loutsenhizer Arroyo
Gunnison Gorge National Conservation Area
SPRING CREEK MESA
Km
0
2.5
5
10

E4

F3

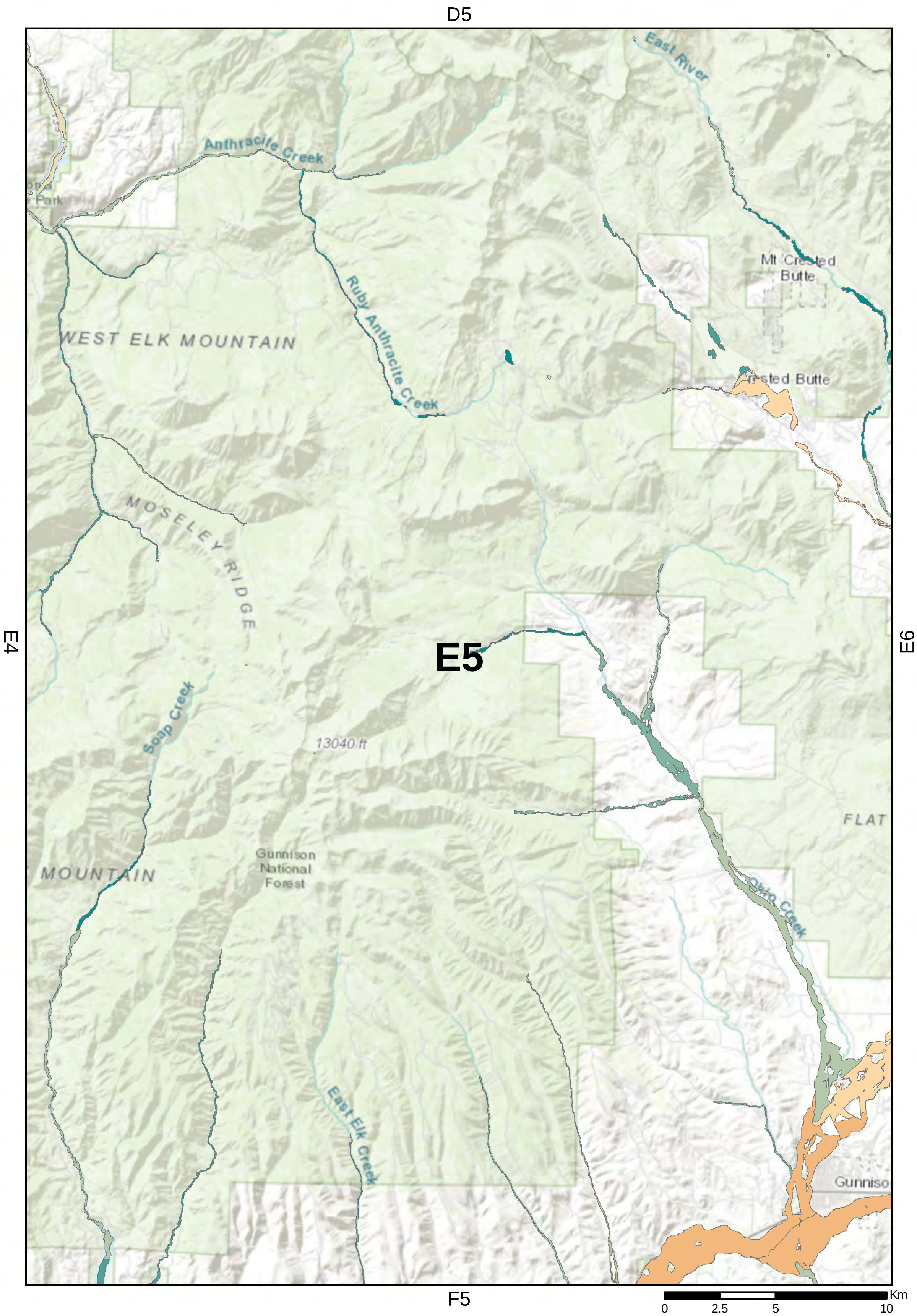
D4

E3


BUCK MESA
Leroux Creek
Somerset
OAK MESA
Paonia
133
Hotchkiss
GERS MESA
Lazear
11401 ft
E4
92
DELTA
Smith Fork
Crawford
FRUITLAND MESA
WEST ELK
Black Canyon
of the Gunnison
National Park
92
Crystal Creek
GUNNISON
BLACK MESA
Km
0
2.5
5
10

E5

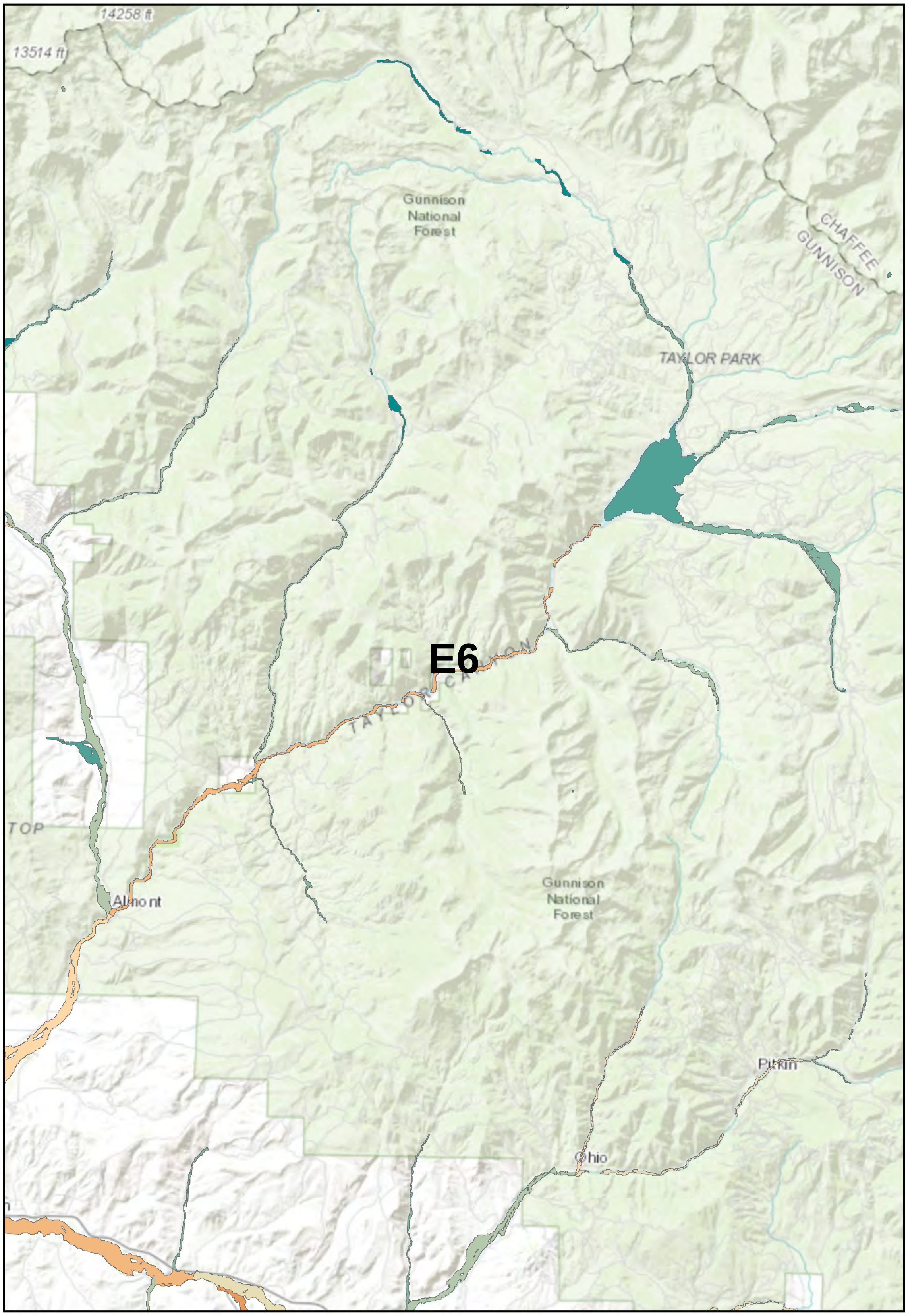
F4



D5
E4
E6
F5
E5
Anthracite Creek
Ruby Anthracite Creek
East River
Mt Crested Butte
rested Butte
WEST ELK MOUNTAIN
MOSELEY RIDGE
Soap Creek
13040 ft
Gunnison National Forest
MOUNTAIN
FLAT
Ohio Creek
East Elk Creek
Gunniso
Park
Km
0
2.5
5
10

D6

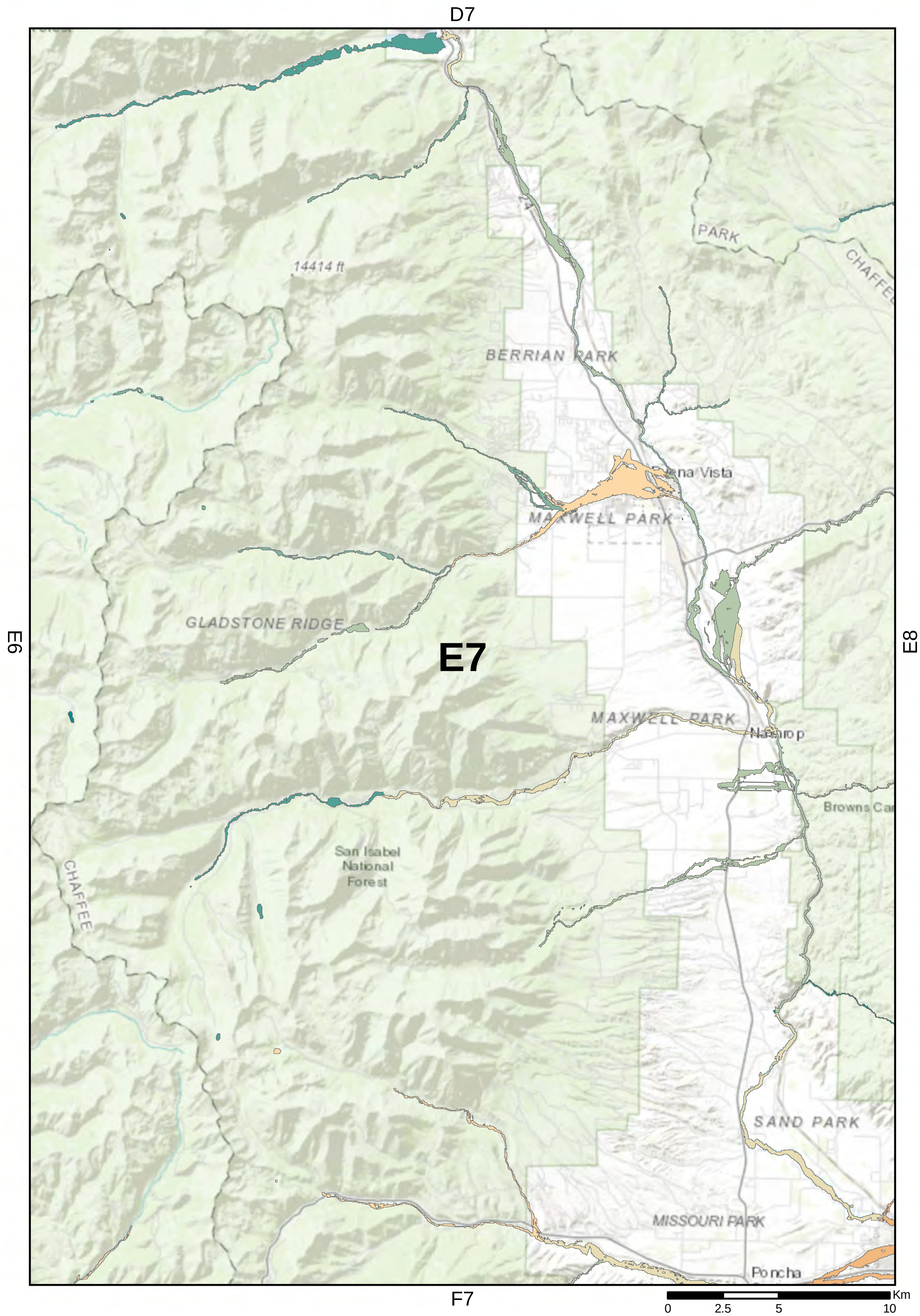
E5



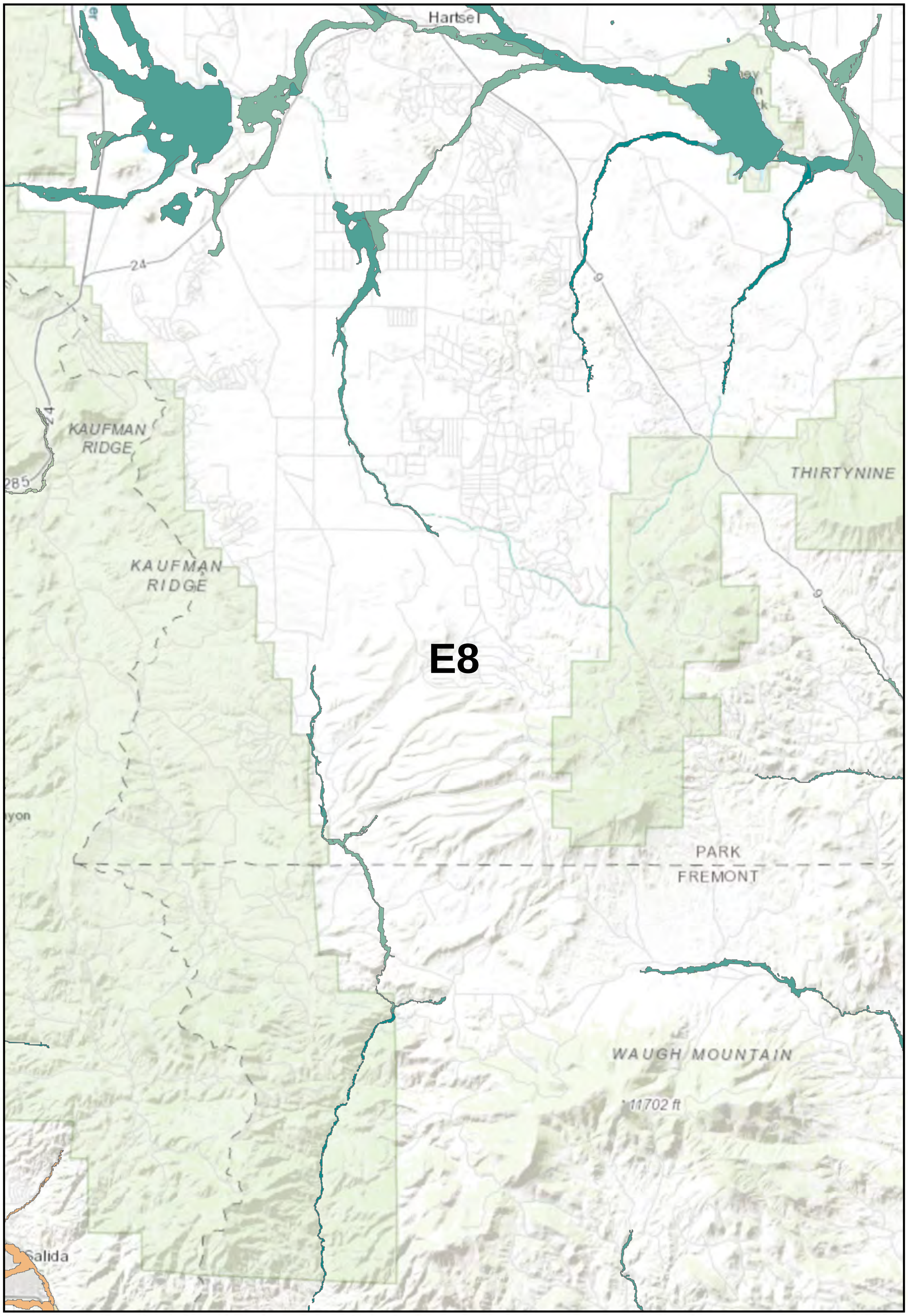
E7

F6

Km
0 2.5 5 10


D7
E6
E8
F7
E7
14414 ft
PARK
CHAFFEE
BERRIAN PARK
Buena Vista
MAXWELL PARK
GLADSTONE RIDGE
MAXWELL PARK
Nathrop
Browns Ca
San Isabel
National
Forest
CHAFFEE
SAND PARK
MISSOURI PARK
Poncha
Km
0
2.5
5
10

D8



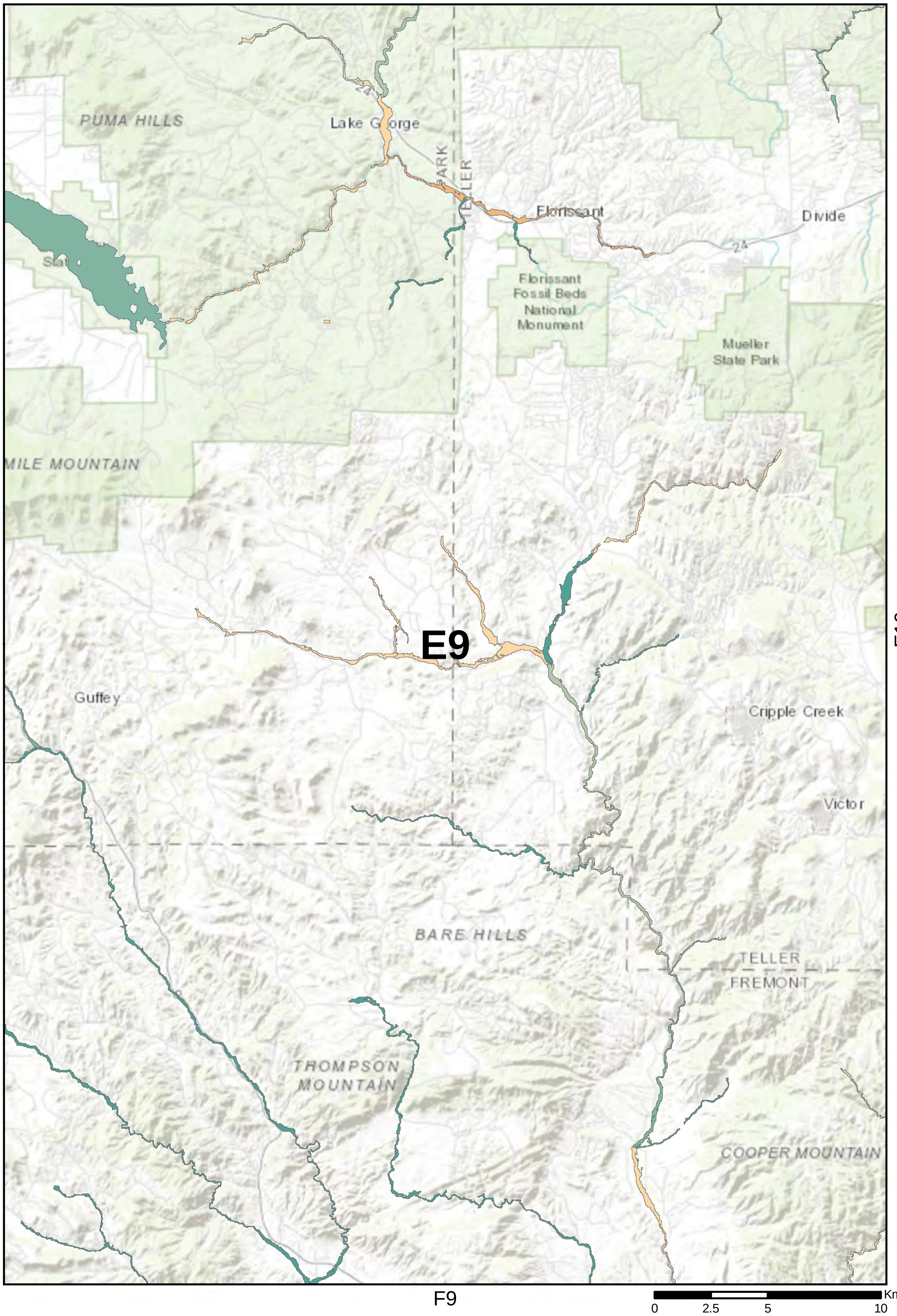
E7

E9

F8

0 2.5 5 10 Km

D9


PUMA HILLS
Lake George
PARK
TELLER
Florissant
Divide
Florissant
Fossil Beds
National
Monument
Mueller
State Park
MILE MOUNTAIN
E9
Guffey
Cripple Creek
Victor
BARE HILLS
TELLER
FREMONT
THOMPSON
MOUNTAIN
COOPER MOUNTAIN
24
Km
0
2.5
5
10

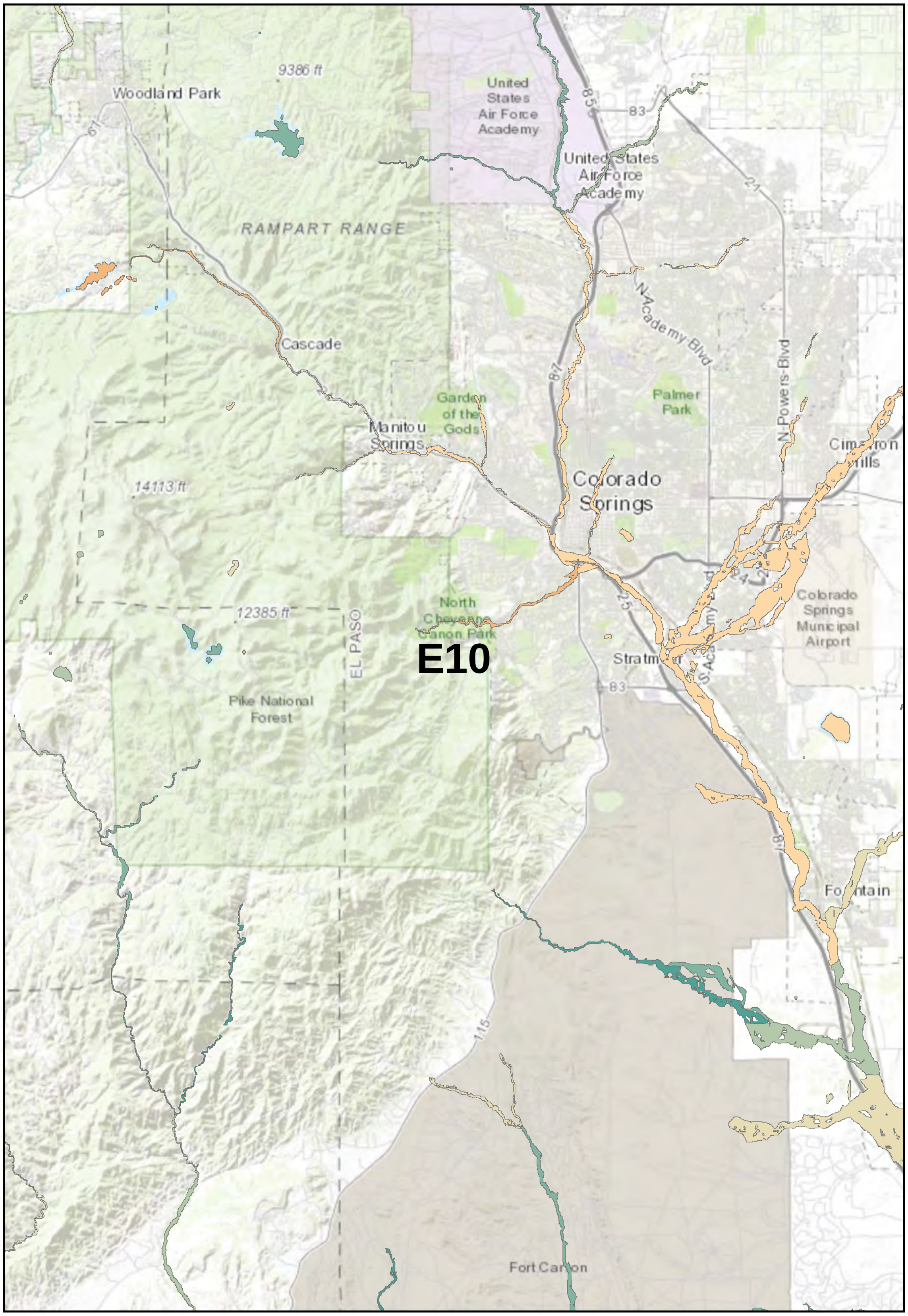
E8

E10

F9

D10

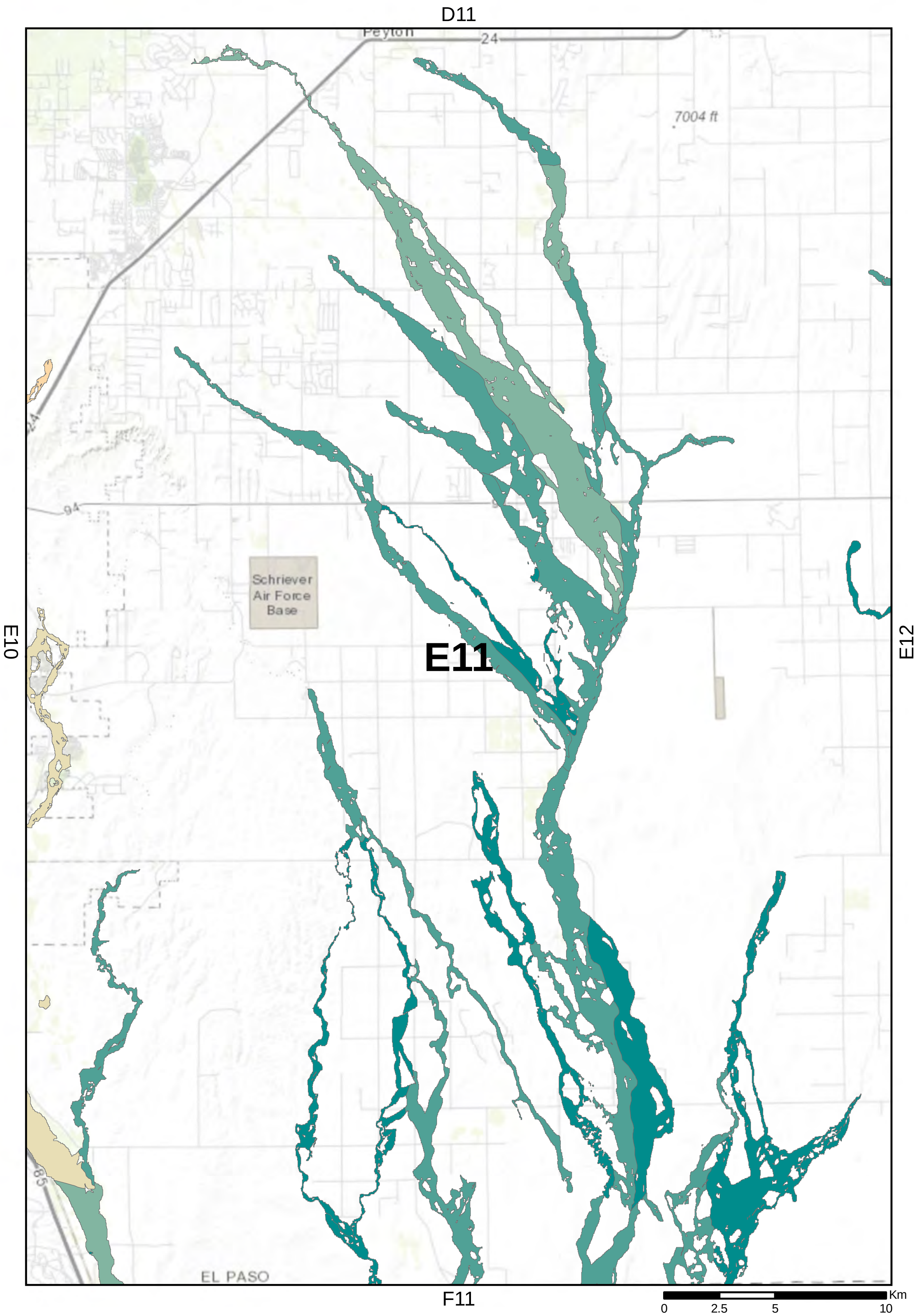
E9

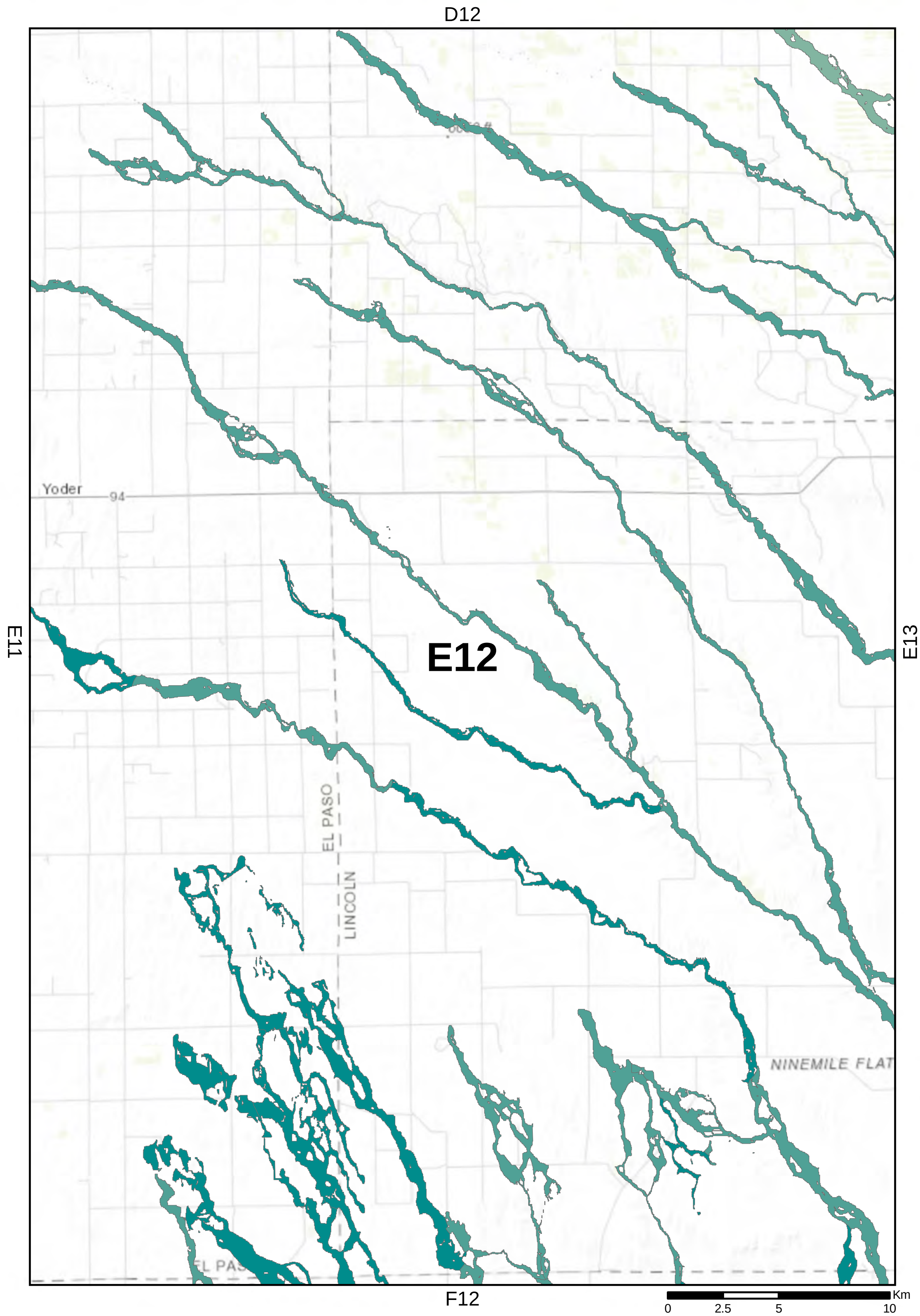


E11

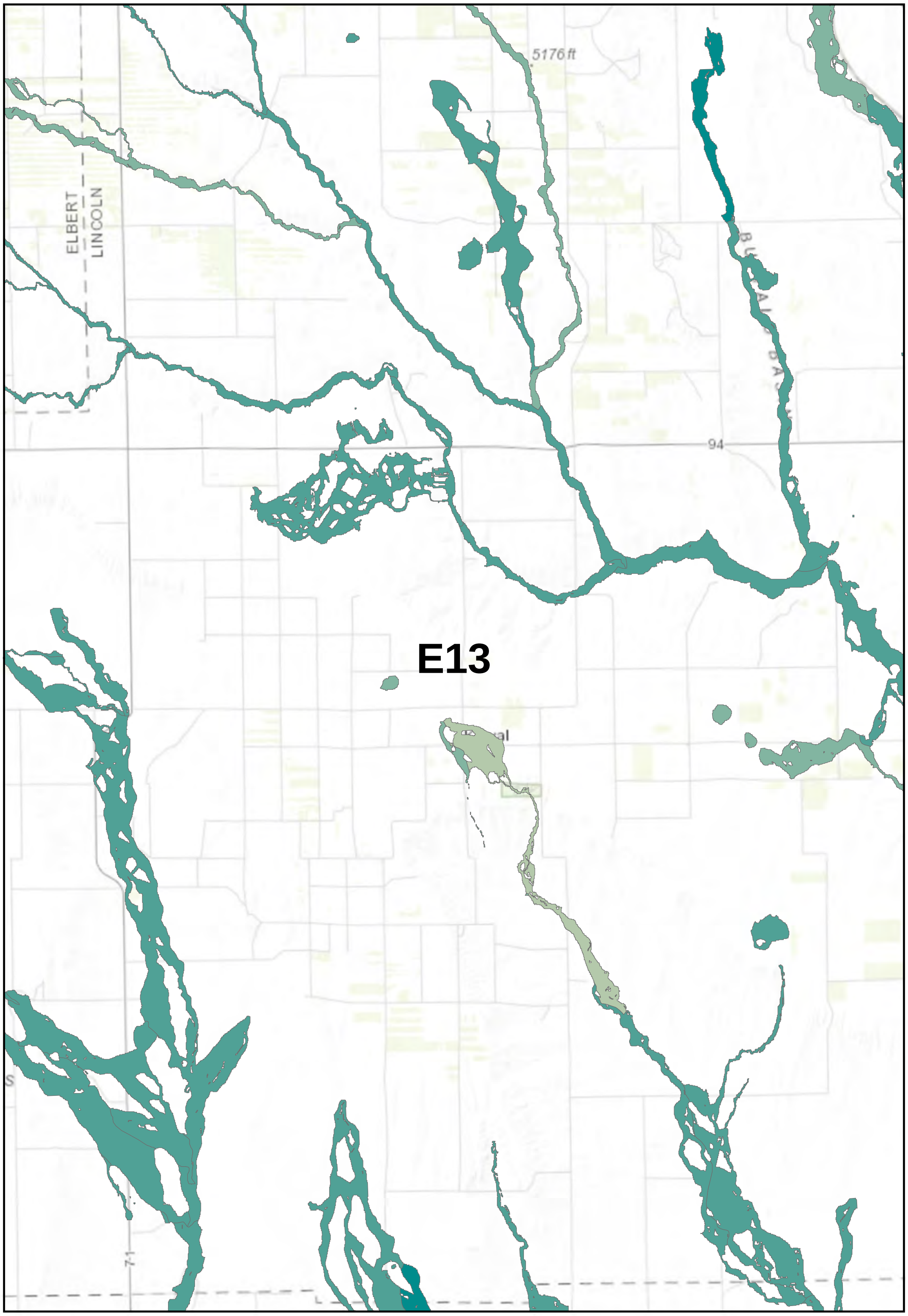
F10

Km
0 2.5 5 10


D11
Peyton
24
7004 ft
94
Schriever
Air Force
Base
E11
E10
E12
85
EL PASO
F11
Km
0
2.5
5
10


D12
E11
E12
E13
F12
Yoder
94
EL PASO
LINCOLN
NINEMILE FLAT
0 2.5 5 10 Km

D13



E12

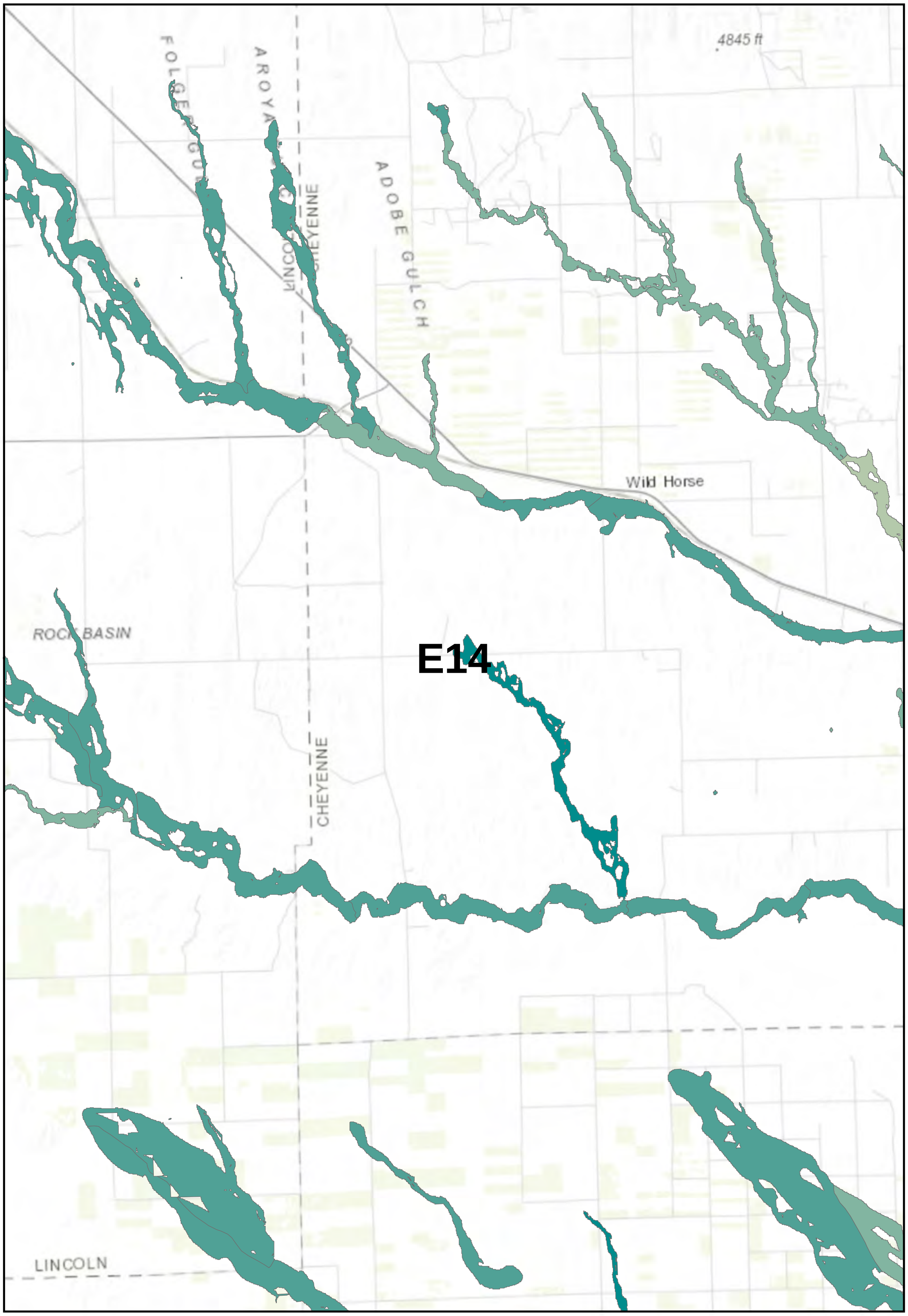
E14

F13

0 2.5 5 10 Km

D14

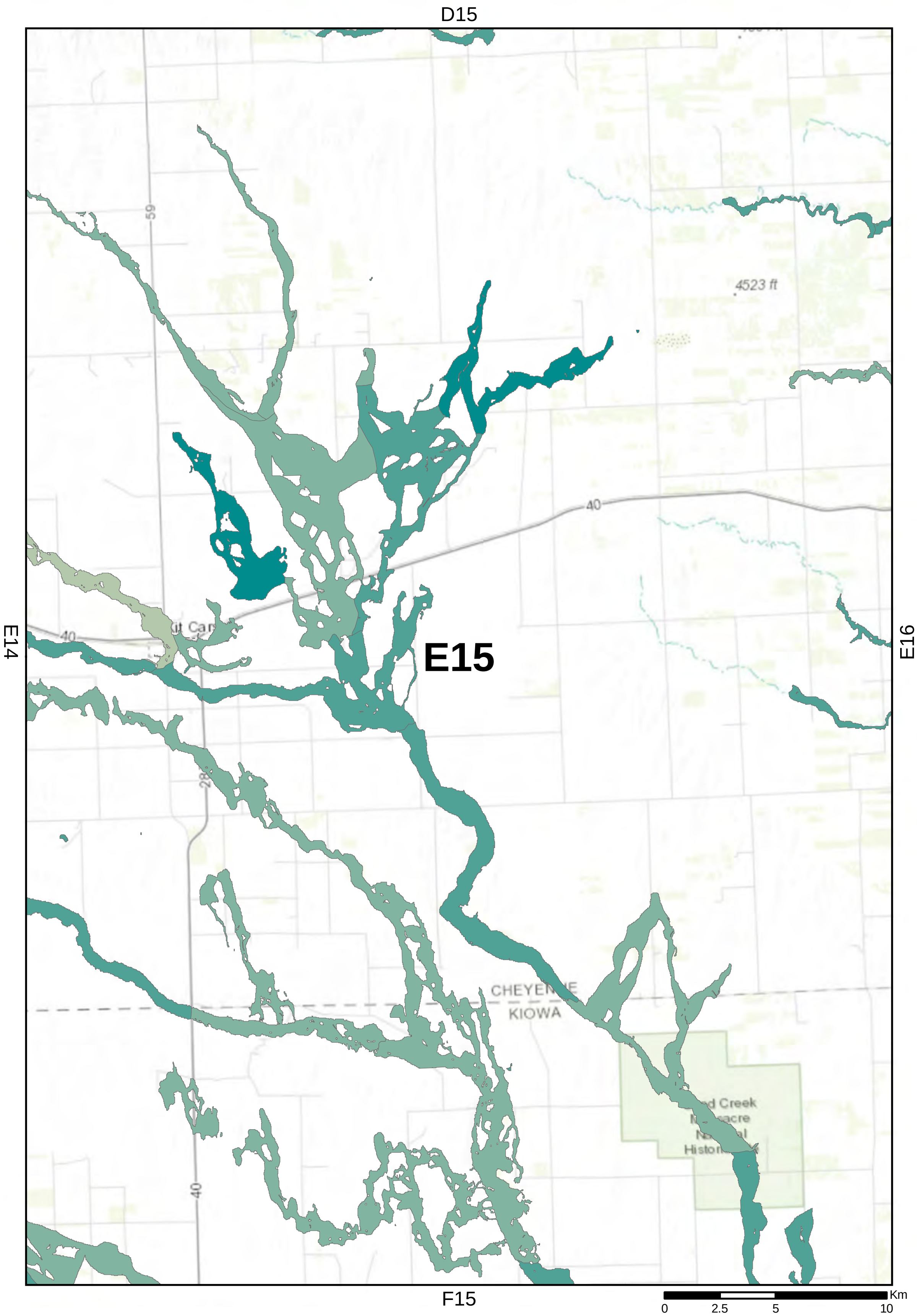
E13



E15

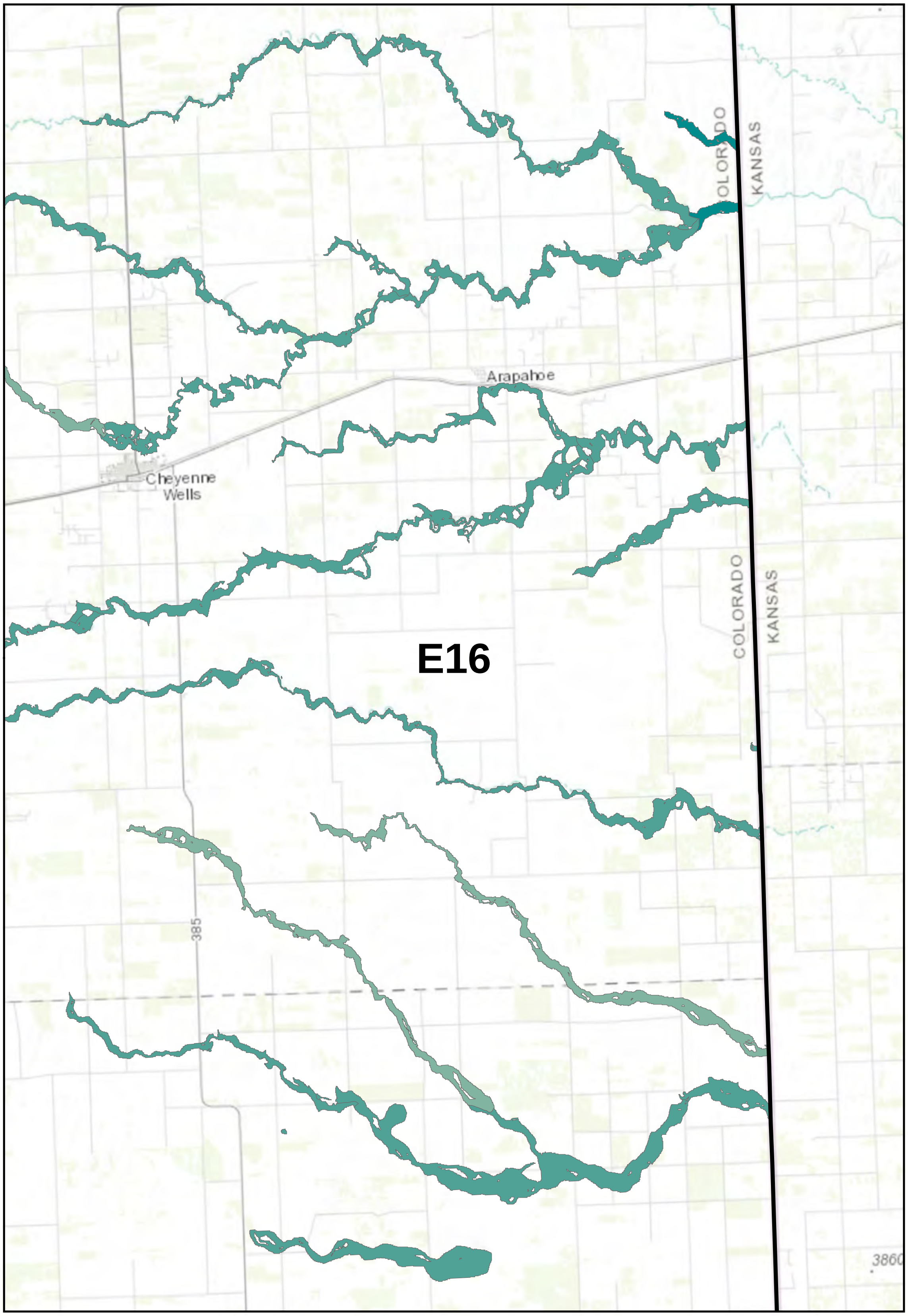
F14

0 2.5 5 10 Km


D15
E14
E15
E16
F15
4523 ft
40
59
287
CHEYENNE
KIOWA
Km
0
2.5
5
10

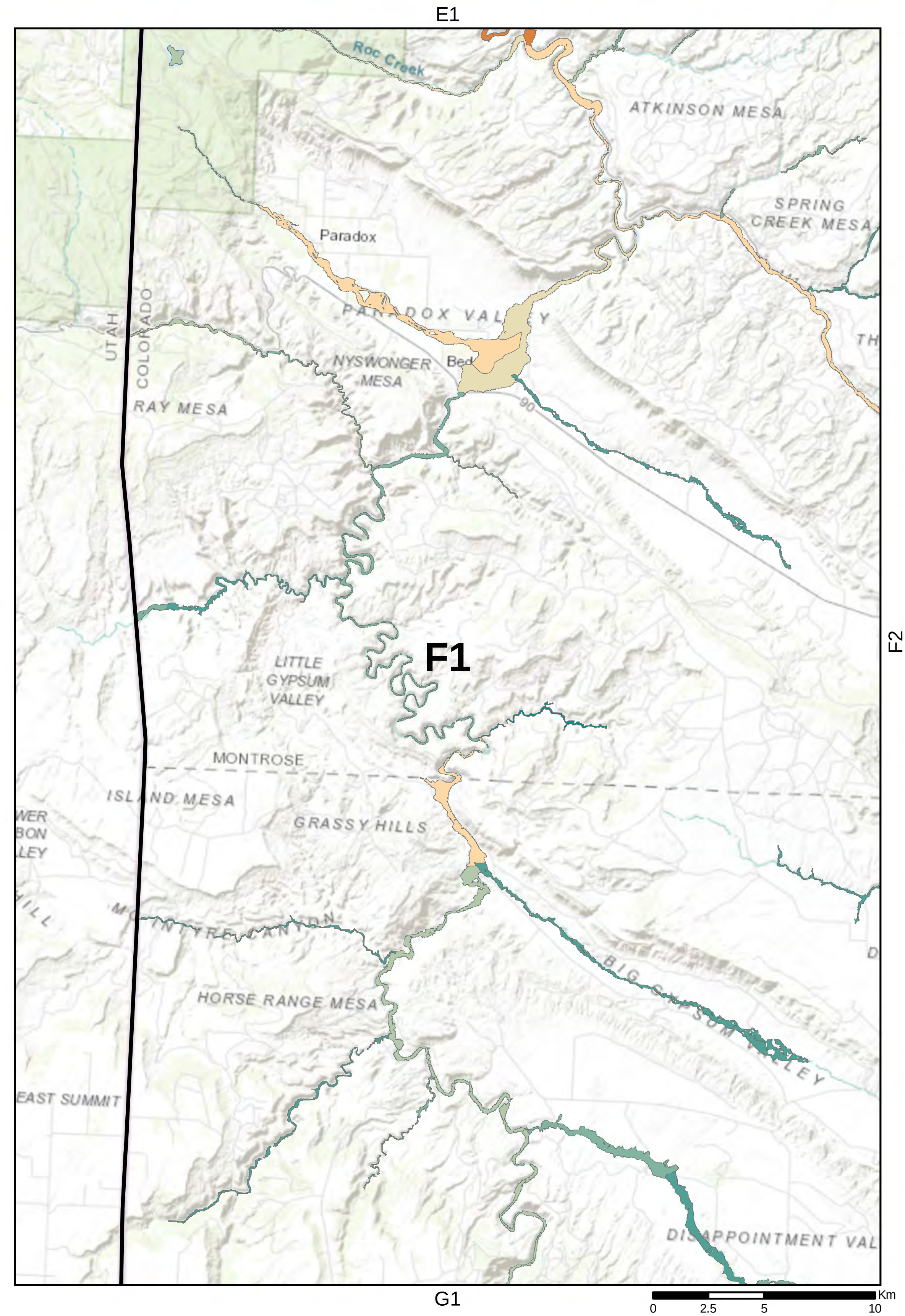
D16

E15



F16

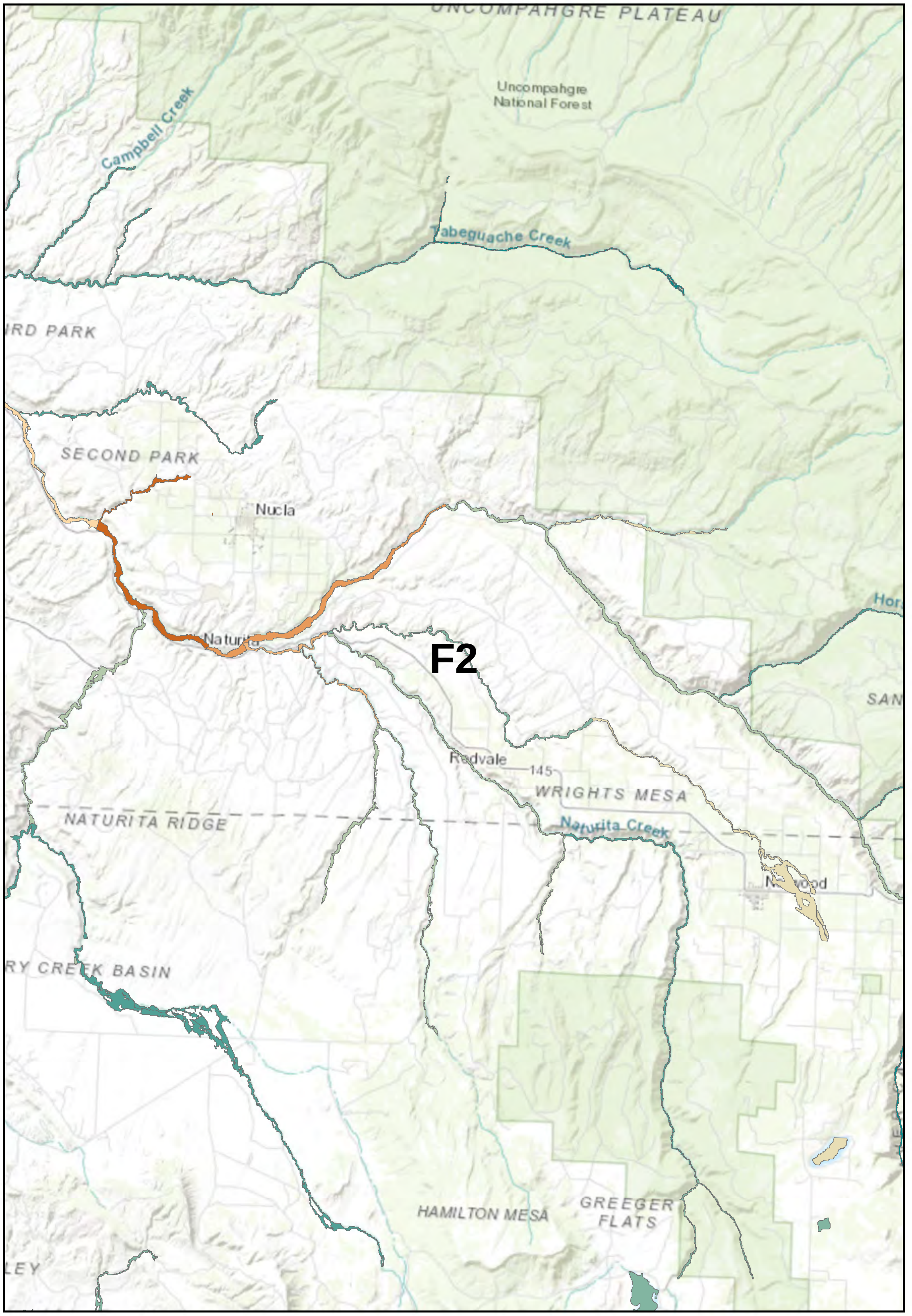
Km
0 2.5 5 10



E1
F2
G1
F1
Roc Creek
ATKINSON MESA
SPRING CREEK MESA
Paradox
PARADOX VALLEY
NYSWONGER MESA
UTAH
COLORADO
RAY MESA
LITTLE GYPSUM VALLEY
MONTROSE
ISLAND MESA
GRASSY HILLS
HORSE RANGE MESA
BIG GYPSUM VALLEY
EAST SUMMIT
DISAPPOINTMENT VAL
Km
0
2.5
5
10

E2

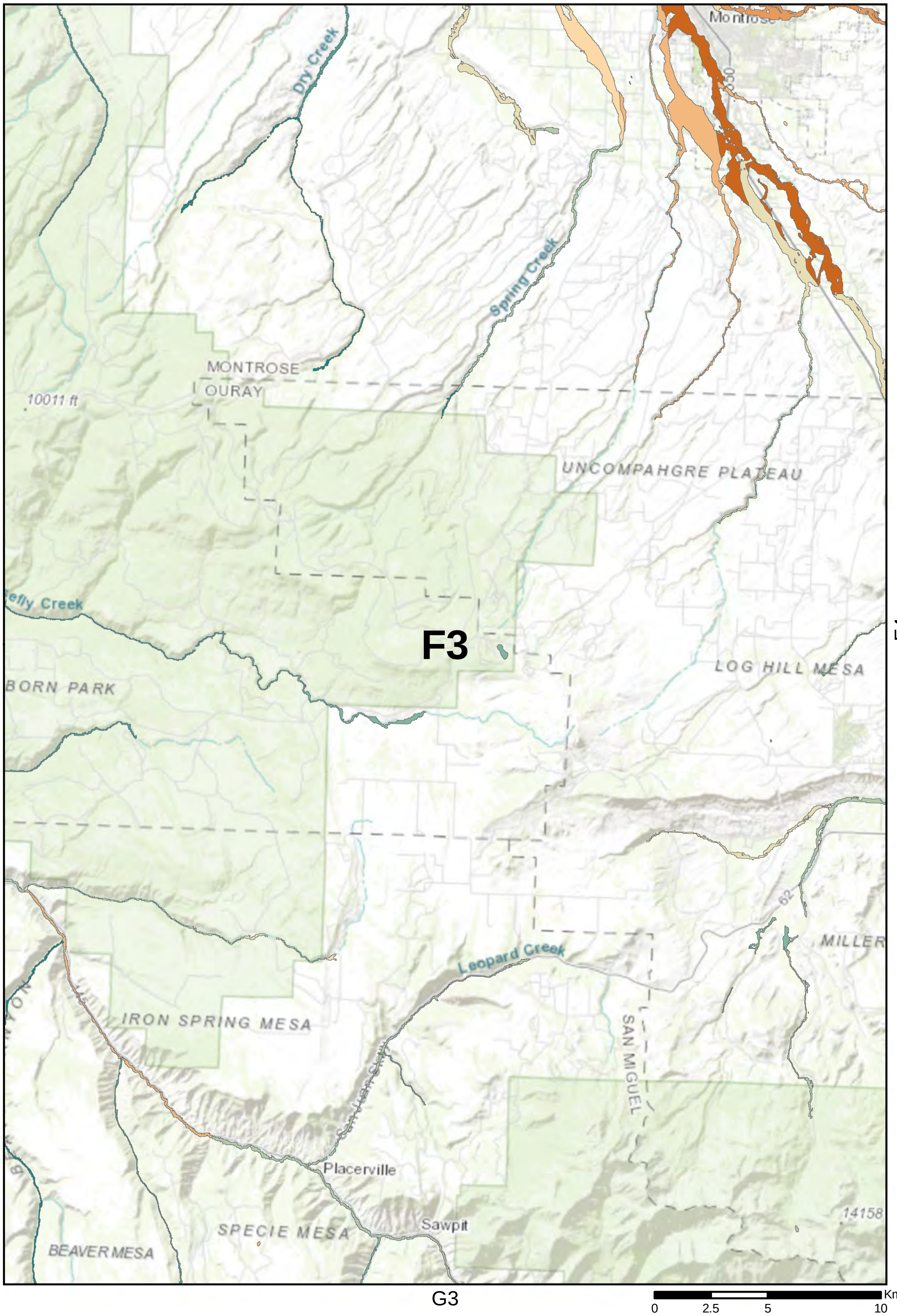
F1


UNCOMPAHGRE PLATEAU
Uncompahgre
National Forest
Campbell Creek
Tabeguache Creek
IRD PARK
SECOND PARK
Nucla
Naturita
F2
Redvale
145
WRIGHTS MESA
Naturita Creek
NATURITA RIDGE
SAN
RY CREEK BASIN
HAMILTON MESA
GREEGER
FLATS
LEY
Km
0
2.5
5
10

F3

G2

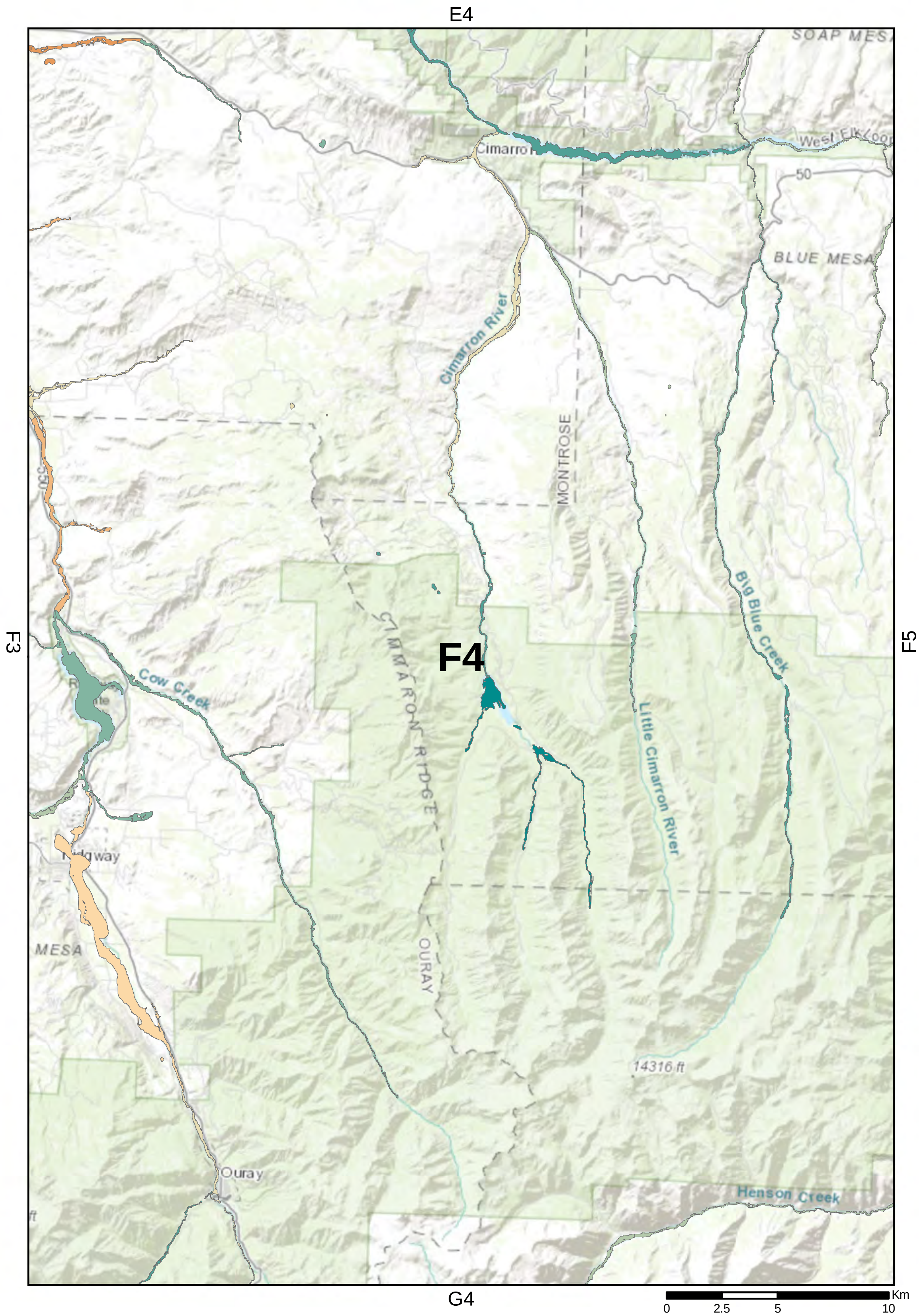
E3


Montrose
Dry Creek
Spring Creek
MONTROSE
OURAY
10011 ft
UNCOMPAHGRE PLATEAU
F3
LOG HILL MESA
BORN PARK
MILLER
Leopard Creek
IRON SPRING MESA
SAN MIGUEL
Placerville
Sawpit
SPECIE MESA
BEAVER MESA
14158
Km
0
2.5
5
10

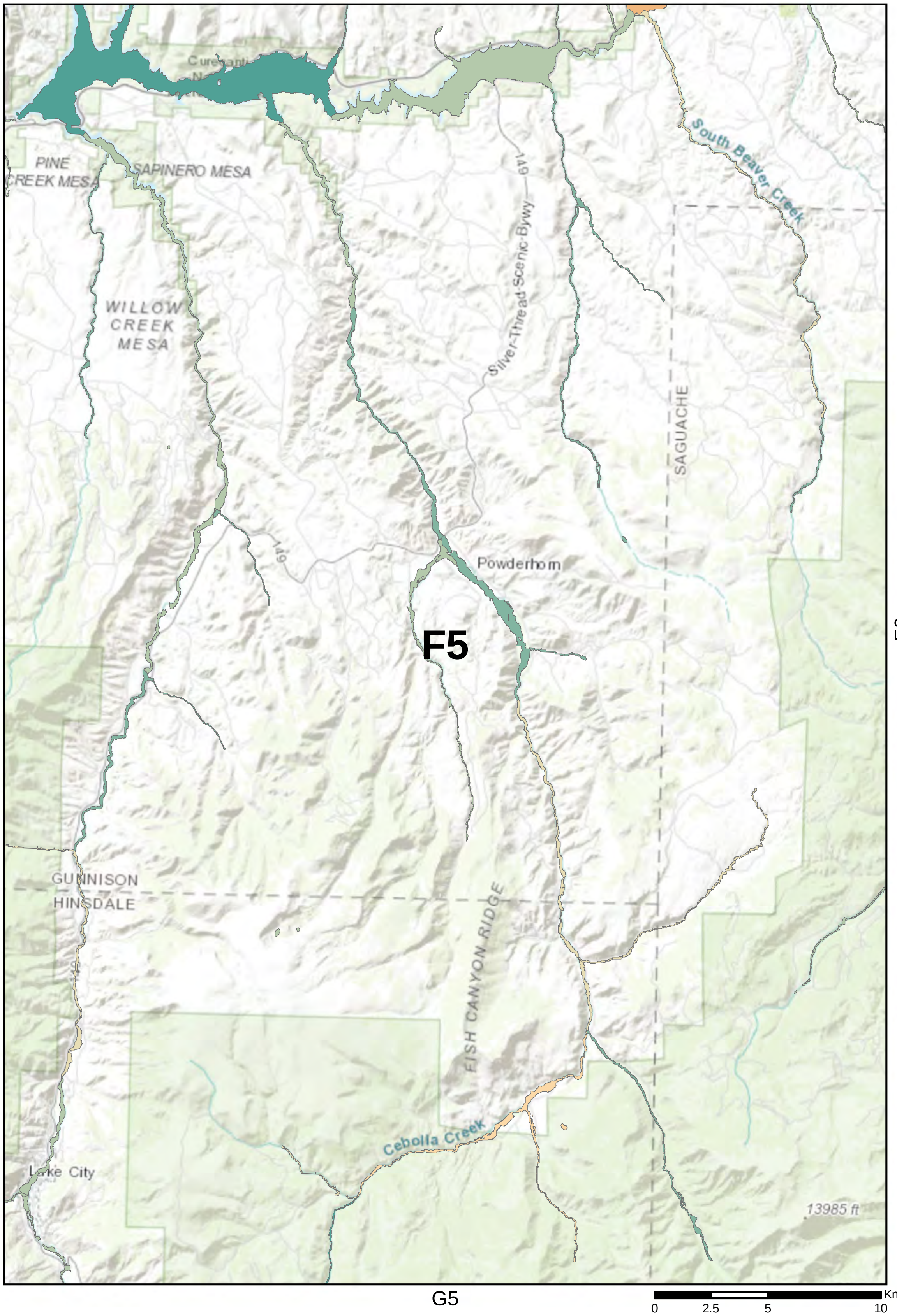
F2

F4

G3


E4
F3
F5
G4
F4
SOAP MESA
Cimarron
50
BLUE MESA
Cimarron River
MONTROSE
Big Blue Creek
Cow Creek
CIMMARON RIDGE
Little Cimarron River
MESA
OURAY
14316 ft
Ouray
Henson Creek
Km
0
2.5
5
10

E5

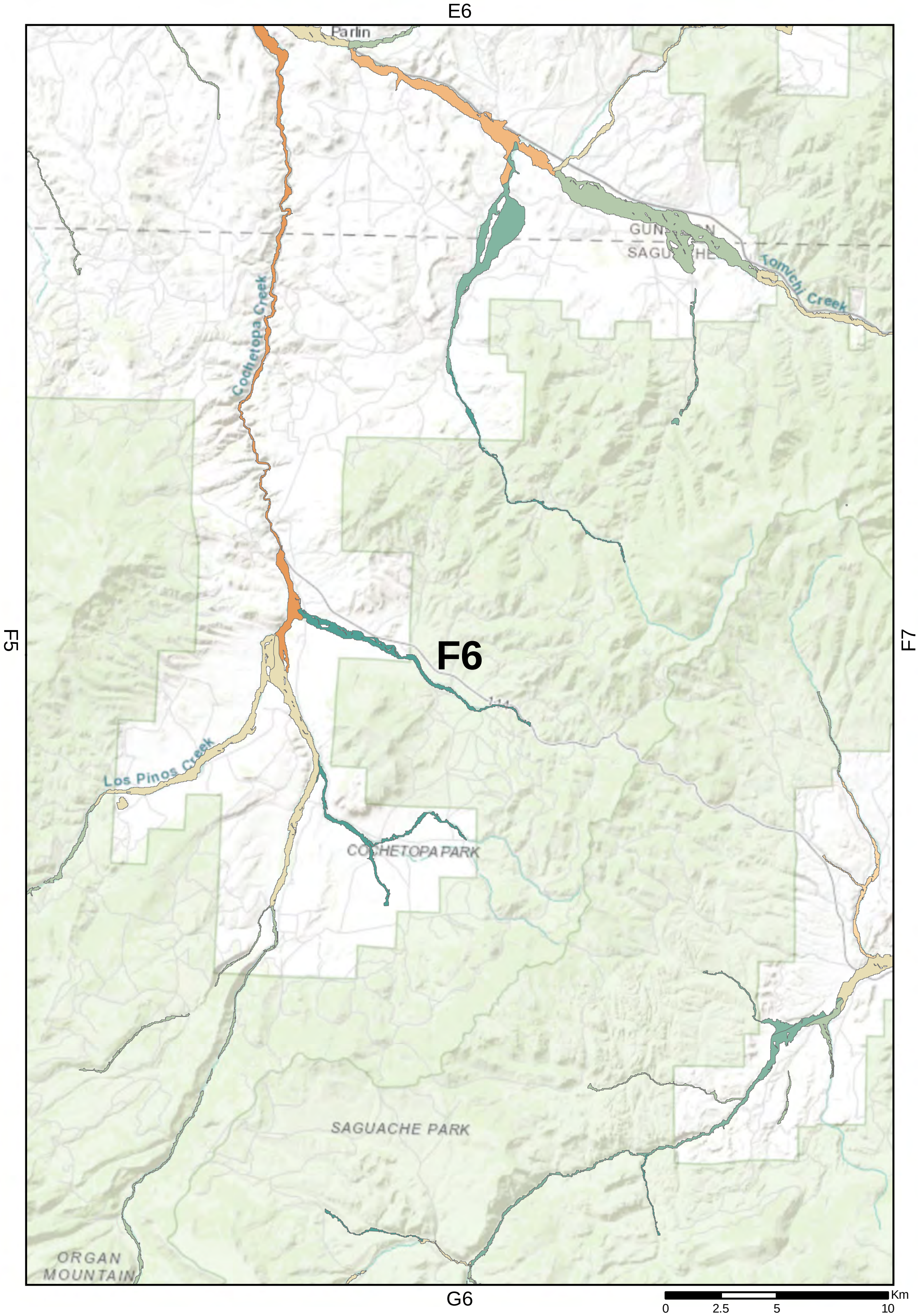

Curecanti
PINE
CREEK MESA
SAPINERO MESA
WILLOW
CREEK
MESA
Silver-Thread Scenic Byway
149
South Beaver Creek
SAGUACHE
Powderhorn
F5
GUNNISON
HINSDALE
FISH CANYON RIDGE
Cebolla Creek
Lake City
13985 ft
0
2.5
5
10
Km

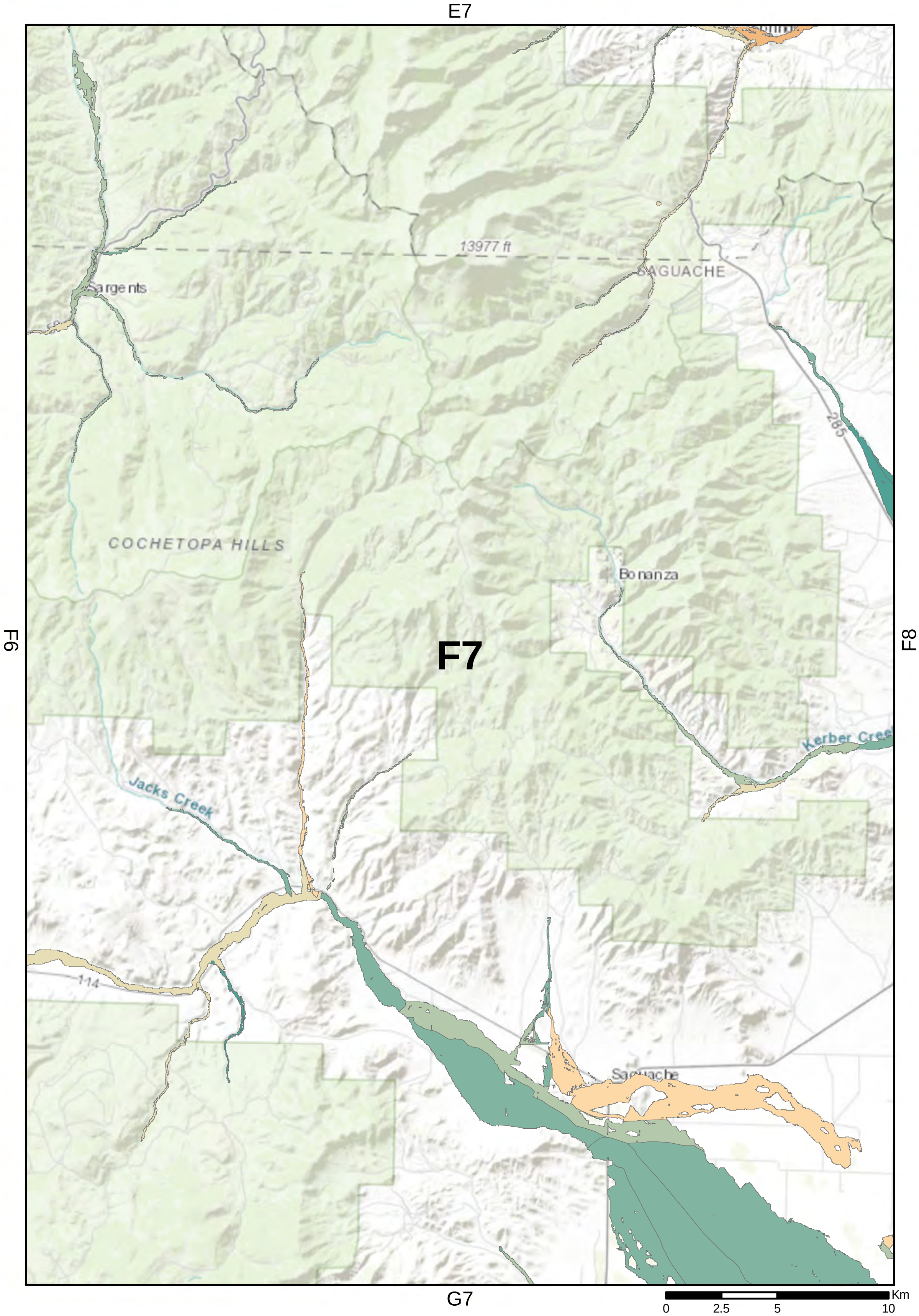
F4

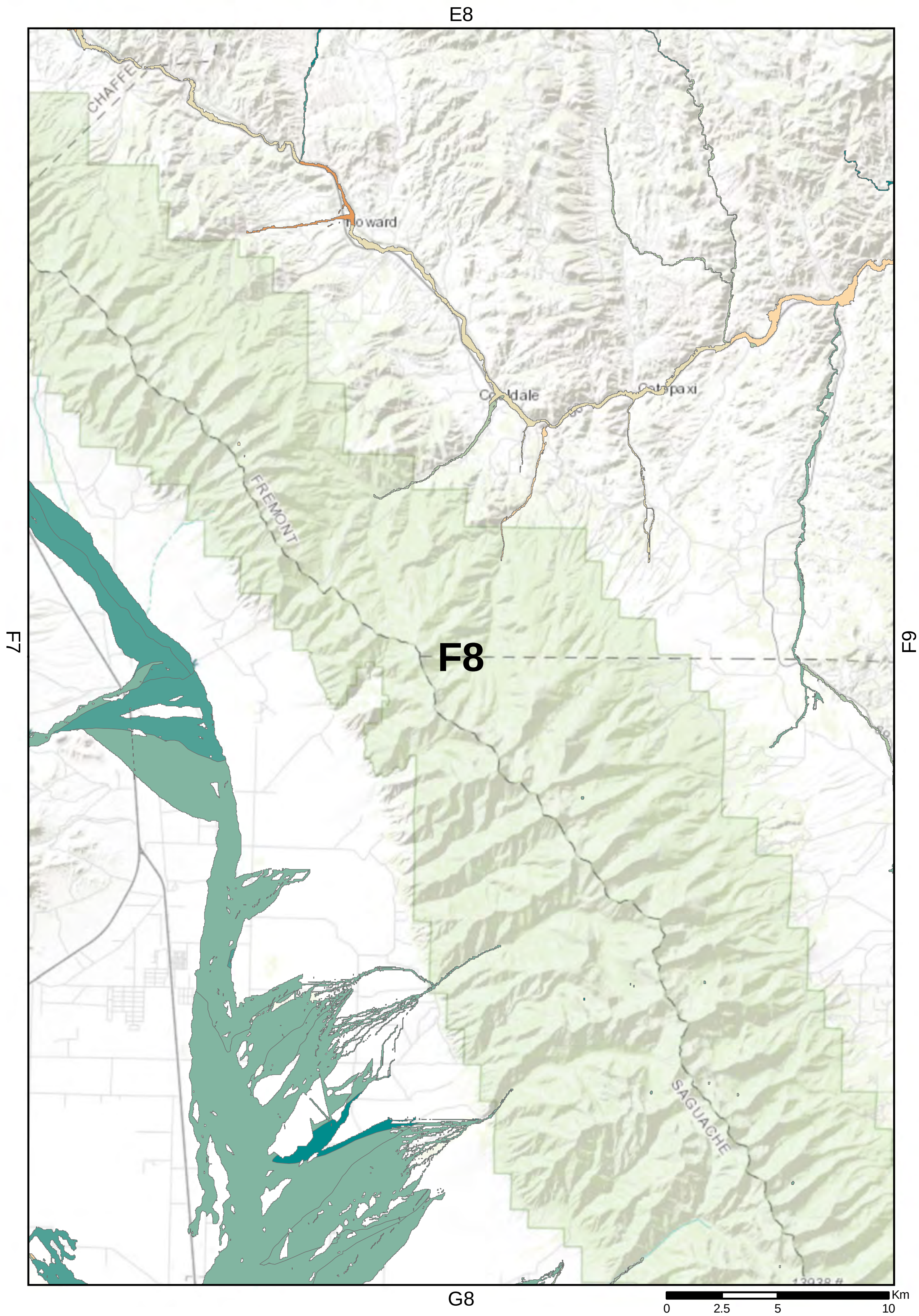
F6

G5

E6

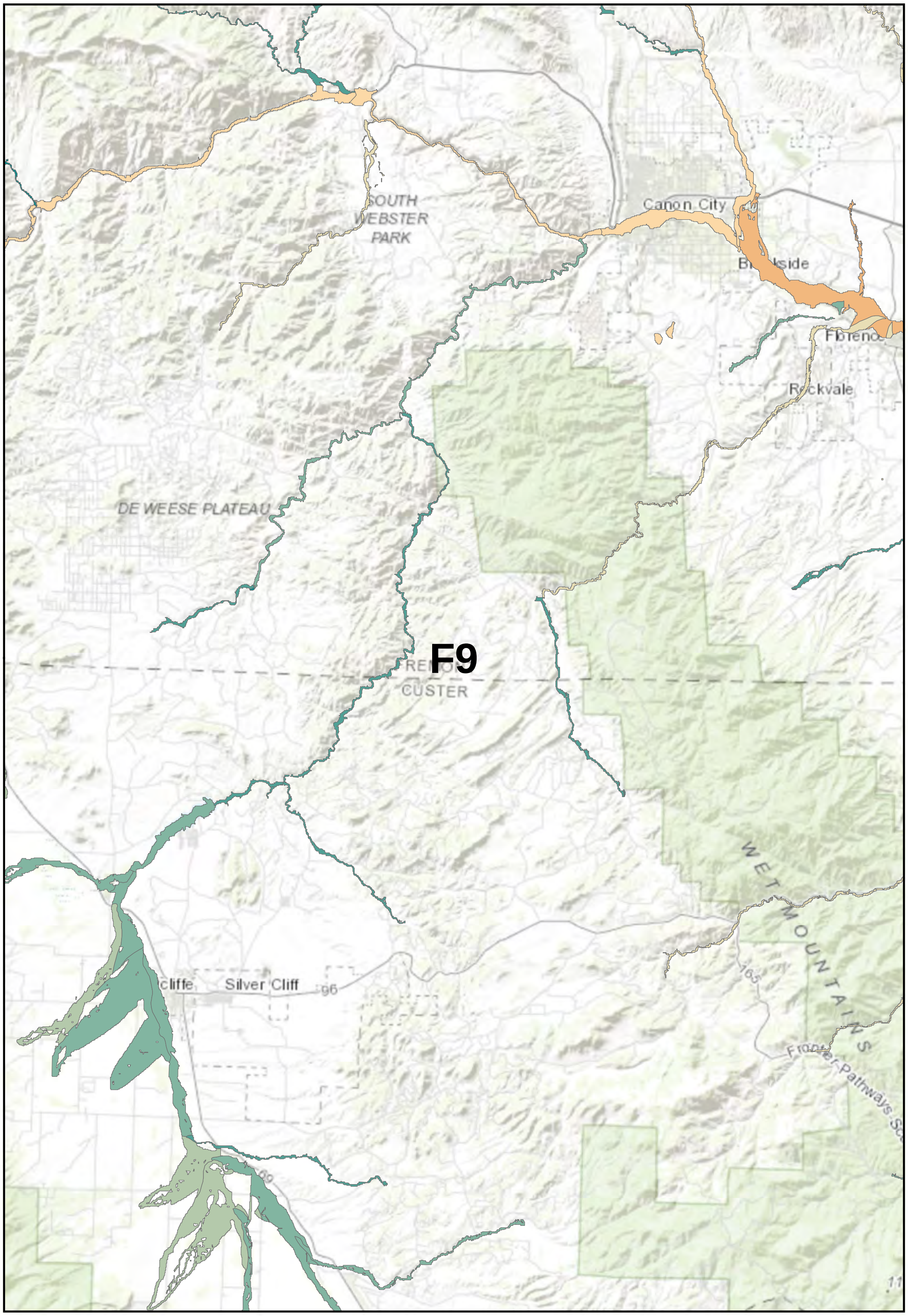

Parlin
Cochetopa Creek
Tomichi Creek
Los Pinos Creek
F6
COCHETOPA PARK
SAGUACHE PARK
ORGAN
MOUNTAIN
F5
F7
G6
0
2.5
5
10
Km


E7
F6
F8
G7
F7
13977 ft
SAGUACHE
Sargents
COCHETOPA HILLS
Bonanza
285
Kerber Cree
Jacks Creek
114
Saguache
Km
0
2.5
5
10


E8
F7
F9
G8
CHAFFEE
Howard
Coaldale
Cotopaxi
FREMONT
F8
SAGUACHE
0 2.5 5 10 Km

E9

F8



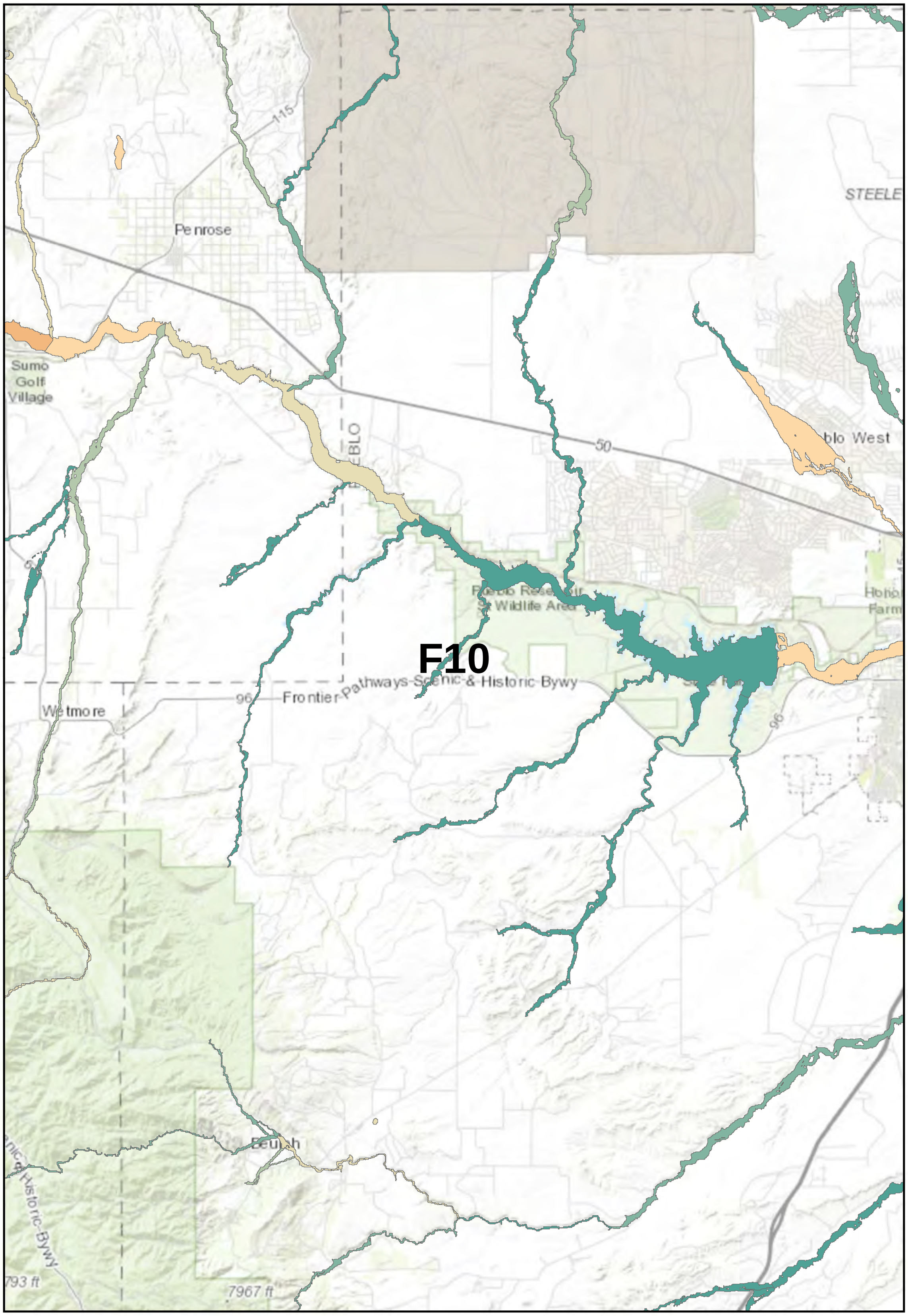
F10

G9

0 2.5 5 10 Km

E10

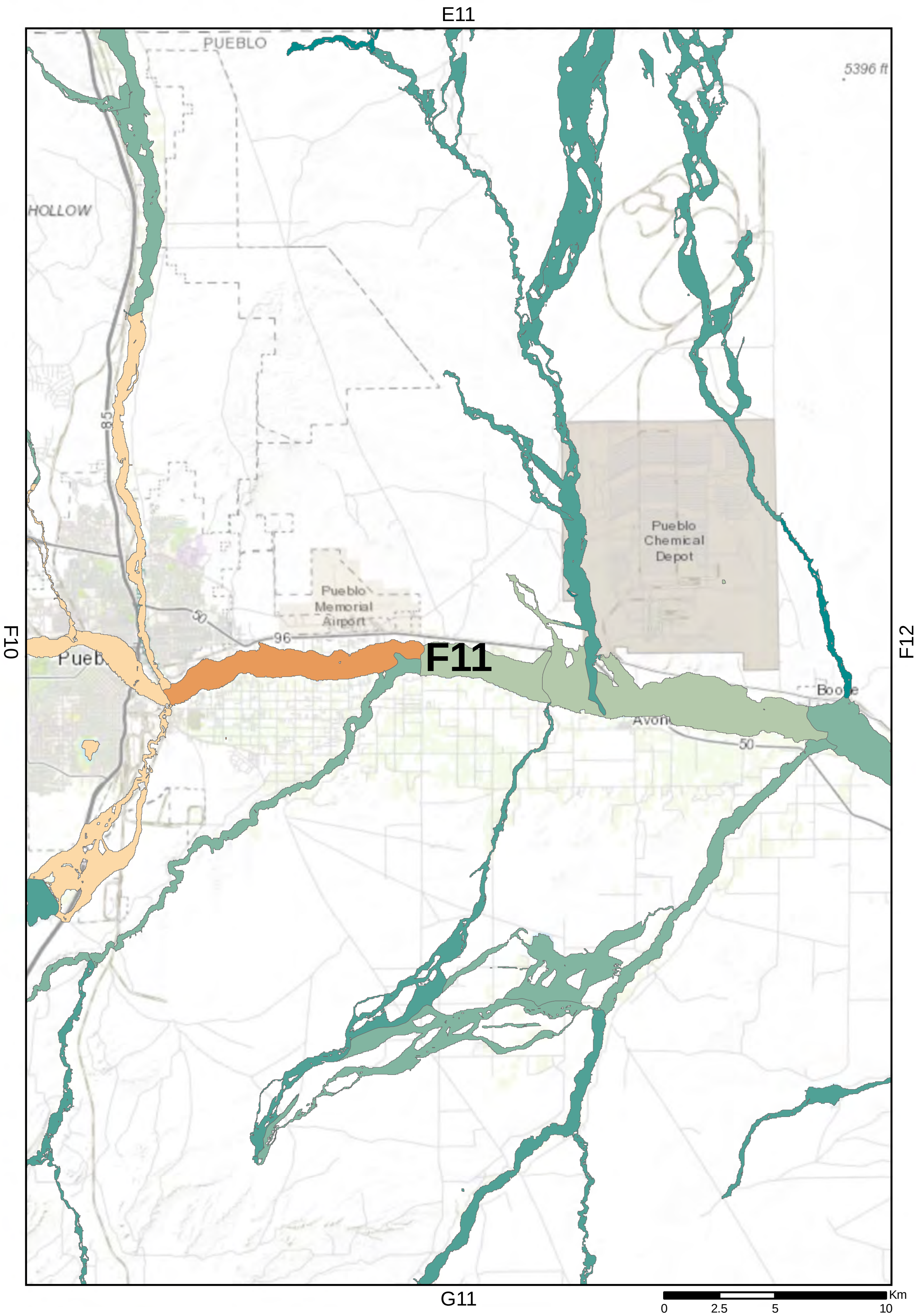
F9



F11

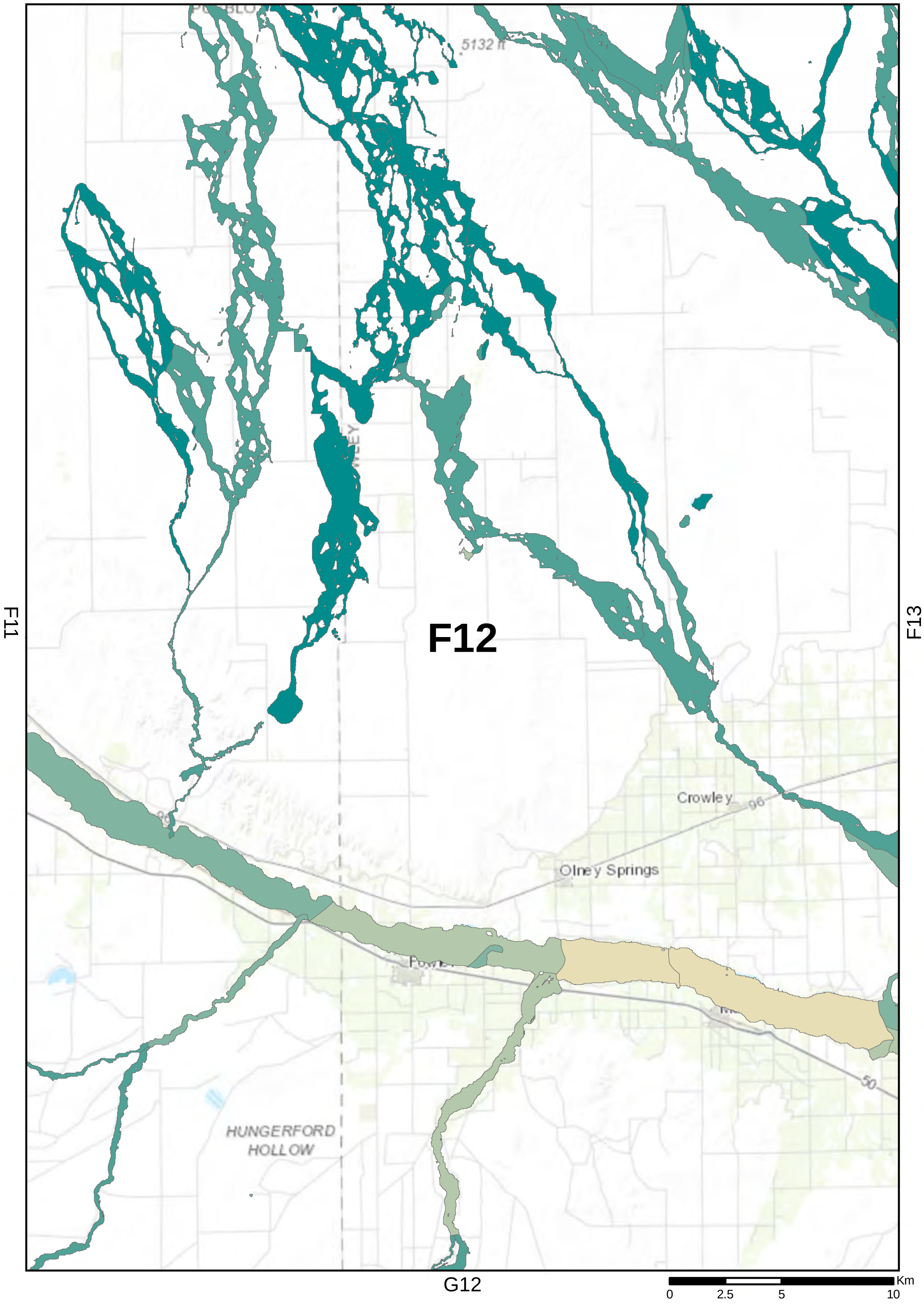
G10

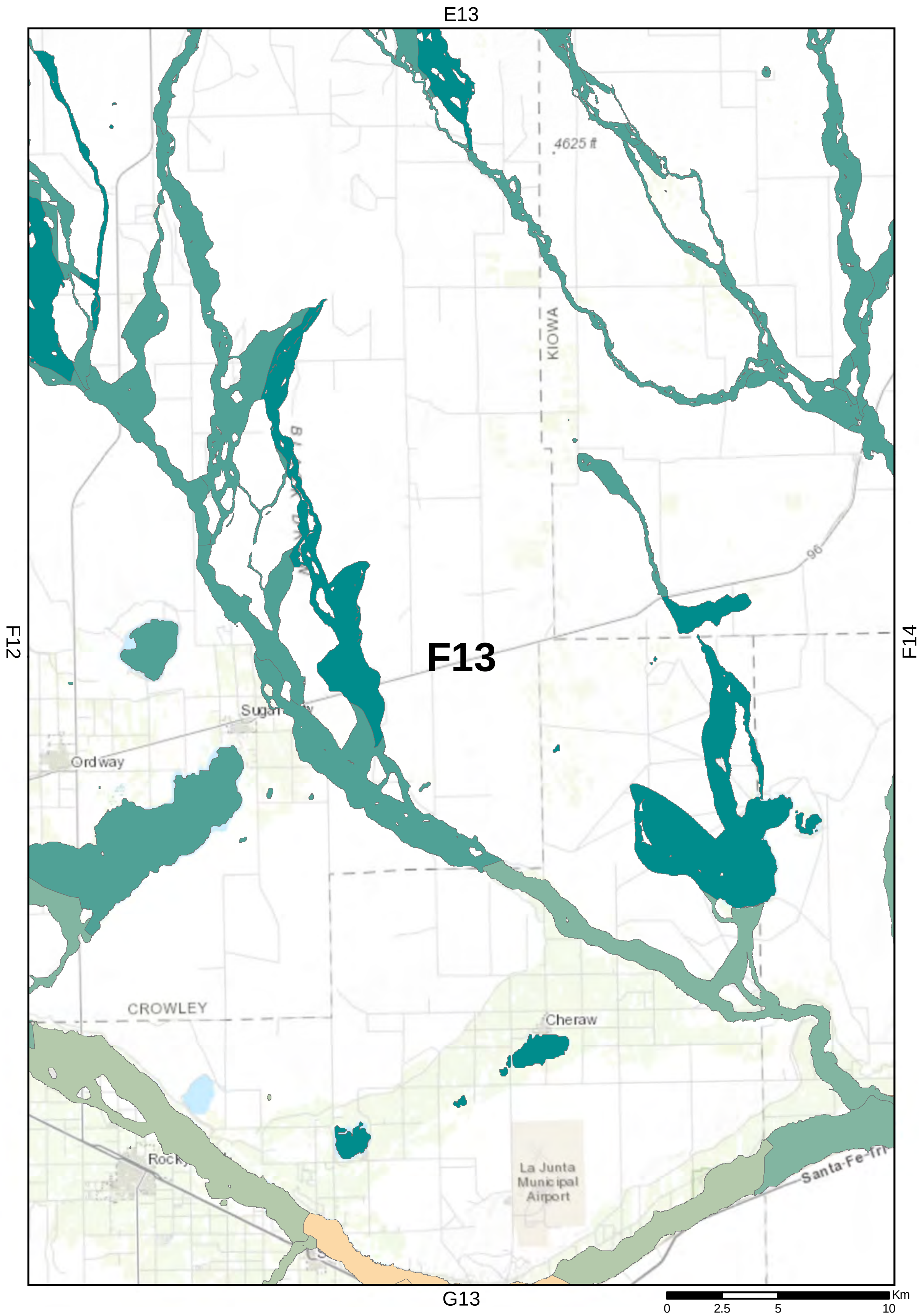
0 2.5 5 10 Km

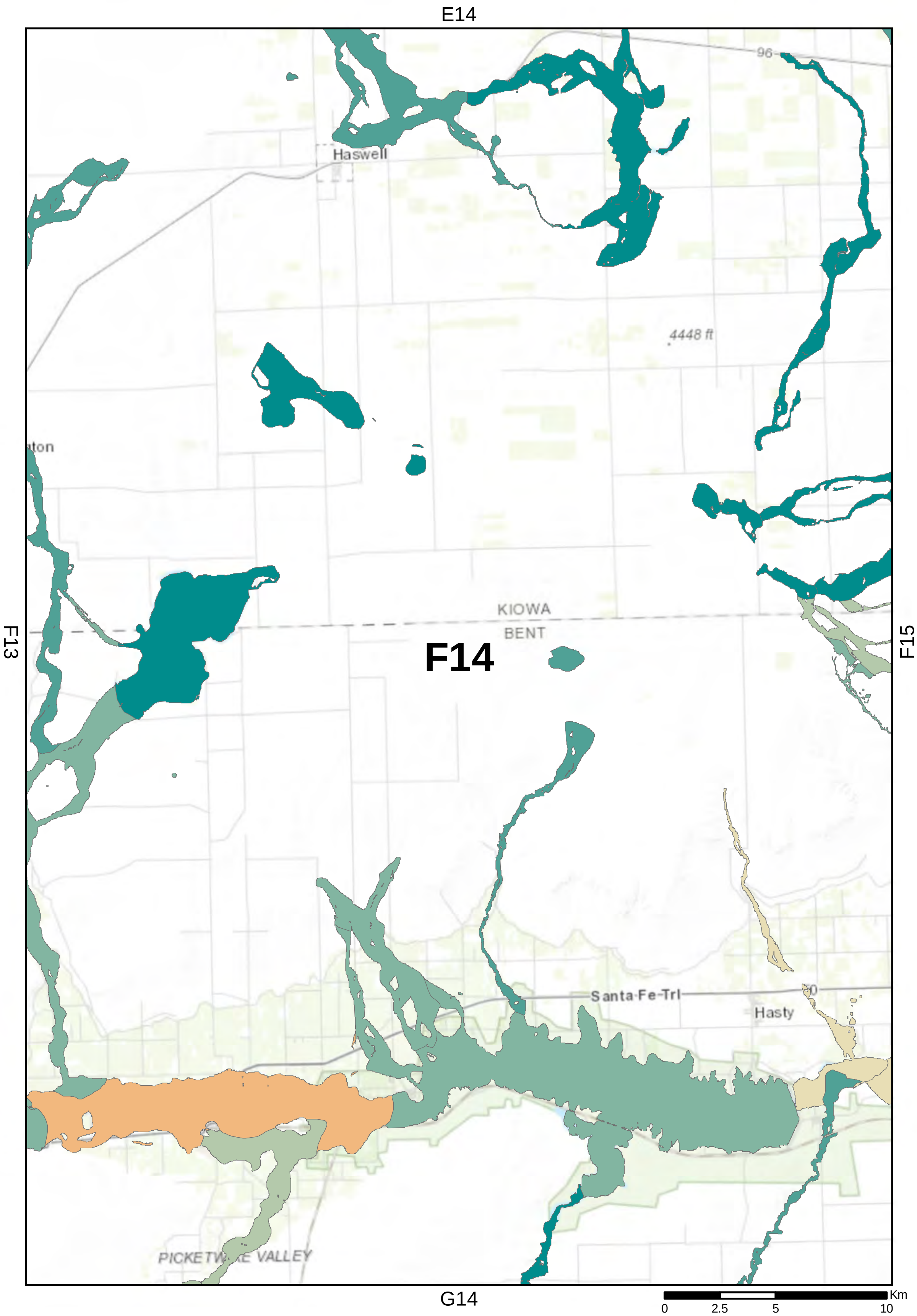


E11
F10
F11
F12
G11
PUEBLO
HOLLOW
5396 ft
Pueblo Chemical Depot
Pueblo Memorial Airport
Pueb
Avon
Boone
85
50
96
0
2.5
5
10
Km

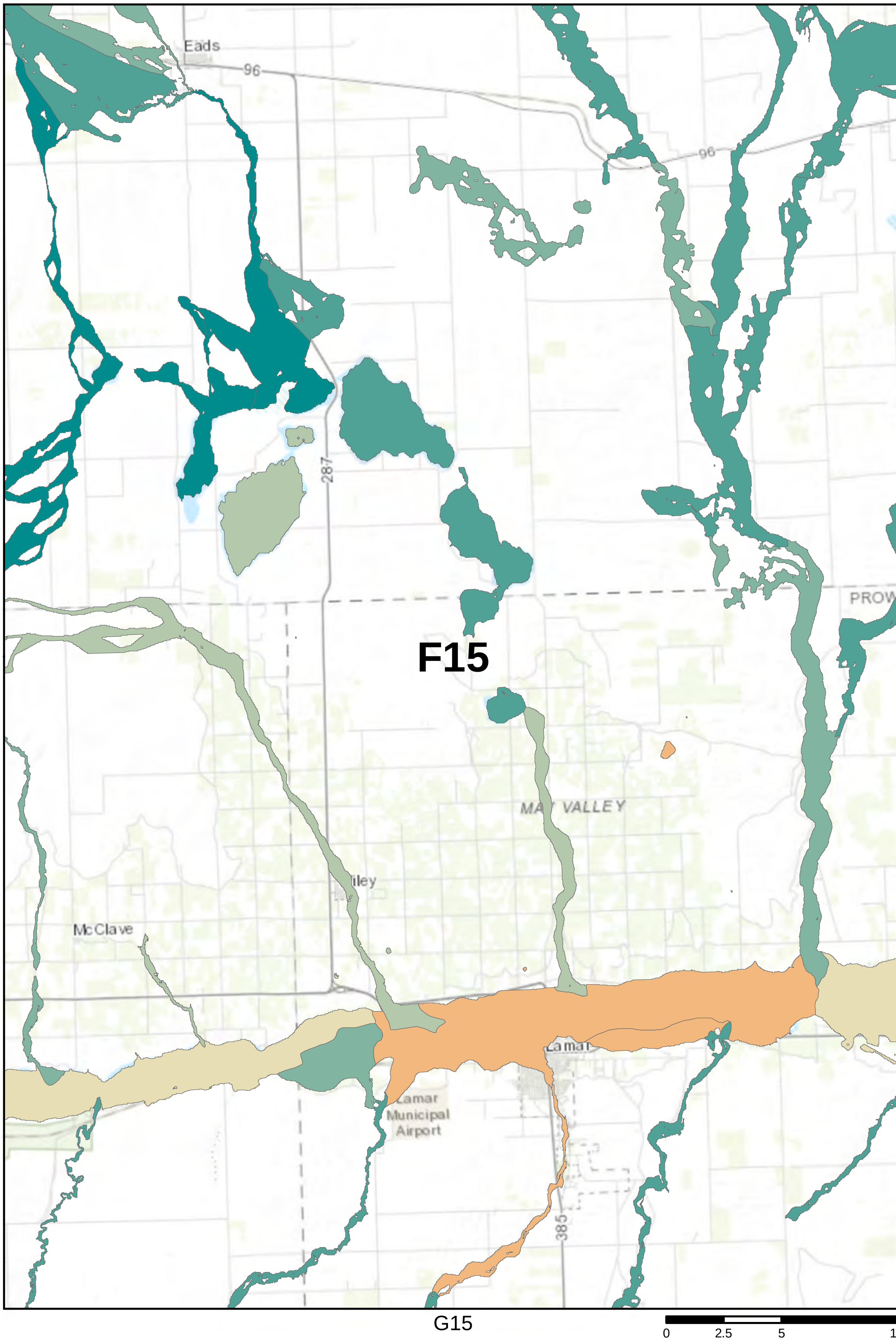
E12


F12
F11
F13
5132 ft
Crowley
Olney Springs
HUNGERFORD HOLLOW
96
50
G12
0
2.5
5
10
Km


E13
F12
F14
G13
F13
4625 ft
KIOWA
96
Ordway
CROWLEY
Cheraw
La Junta
Municipal
Airport
Santa Fe Trl
Km
0
2.5
5
10


E14
Haswell
96
4448 ft
ton
KIOWA
BENT
F14
F13
F15
Santa Fe Trl
Hasty
PICKETW E VALLEY
G14
Km
0
2.5
5
10

E15

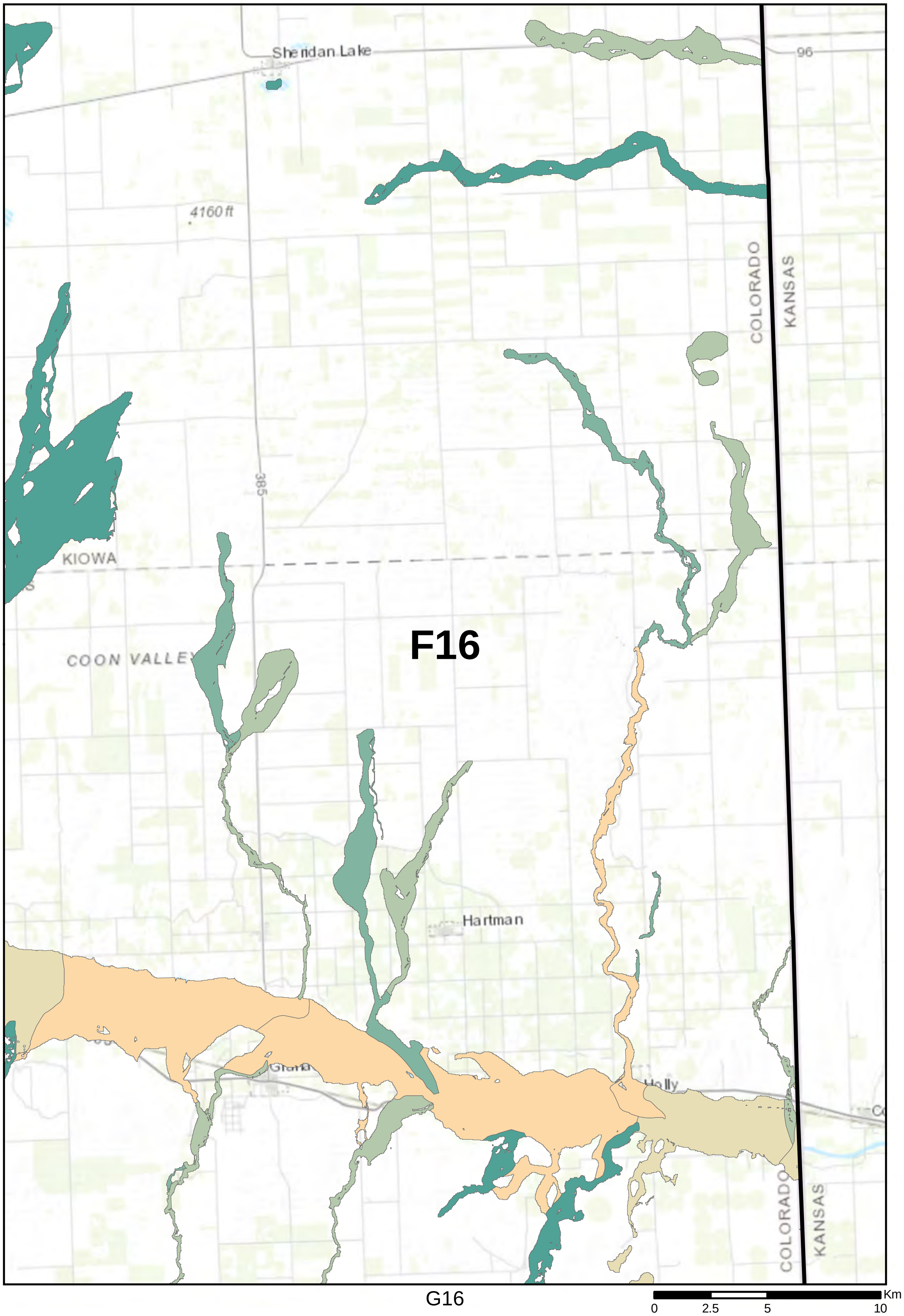


F14

F16

G15

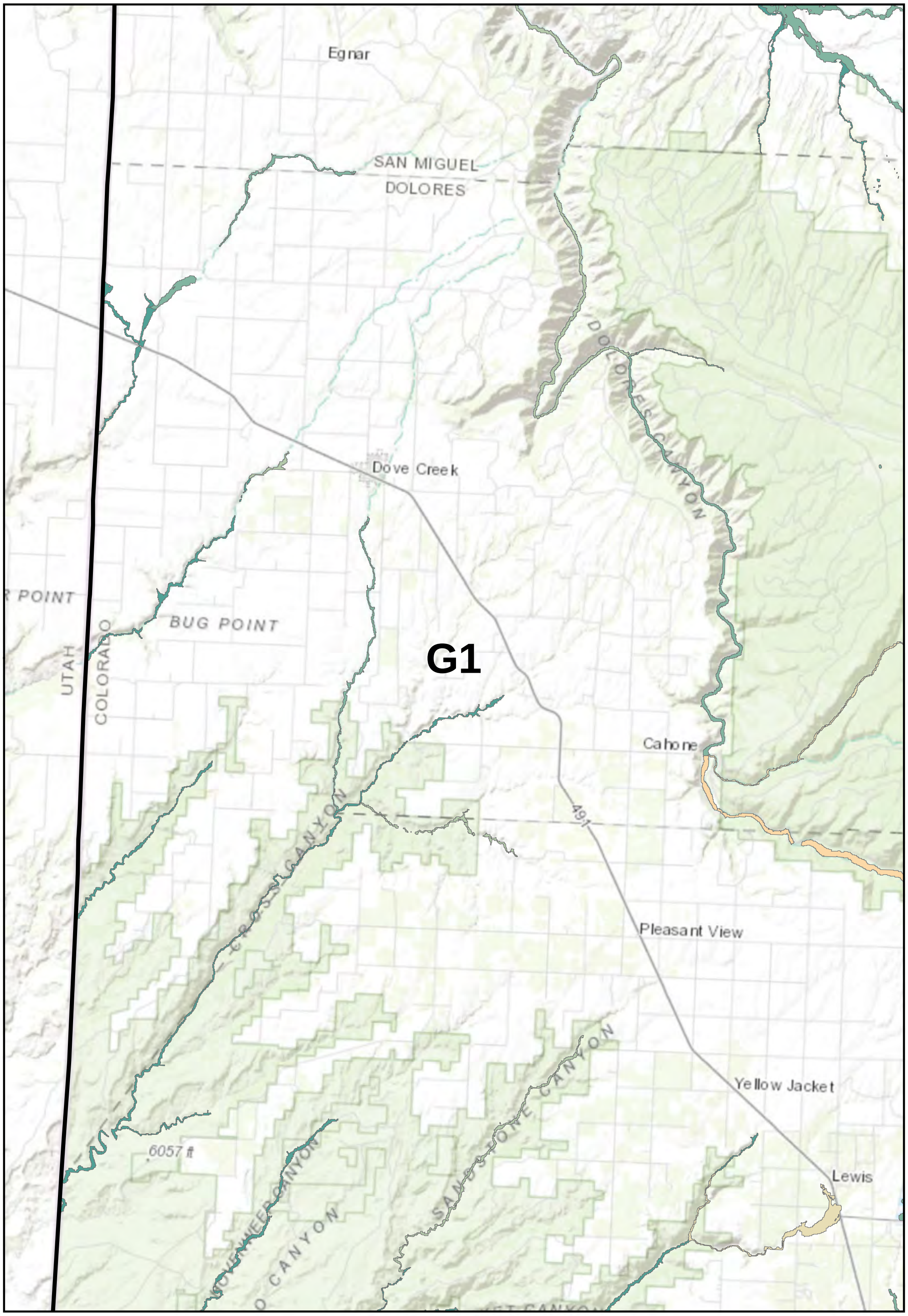
E16


Sheridan Lake
96
4160 ft
385
COLORADO
KANSAS
KIOWA
COON VALLEY
F16
Hartman
Holly
COLORADO
KANSAS
0
2.5
5
10
Km

F15

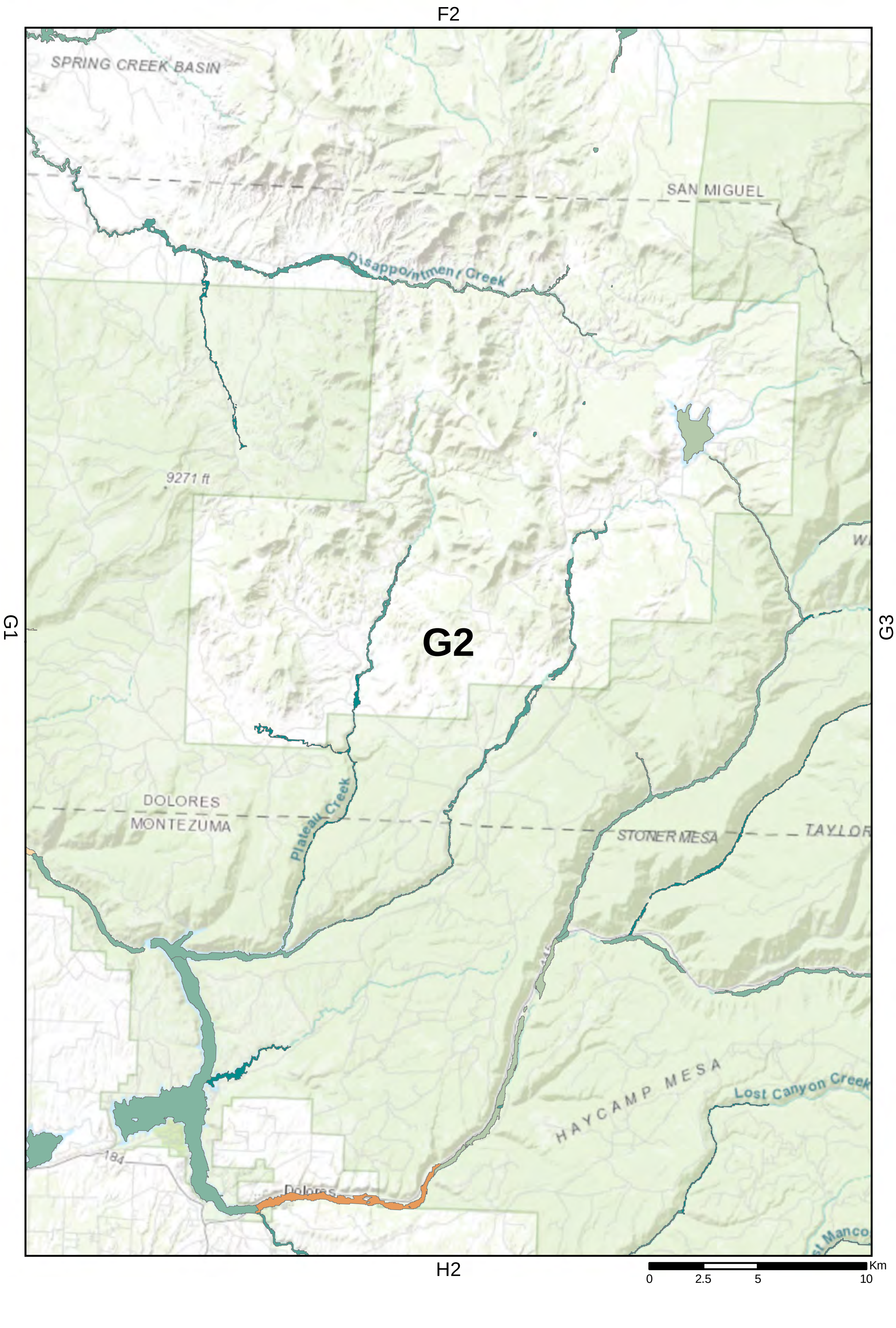
G16

F1


Egnar
SAN MIGUEL
DOLORES
DOLORES CANYON
Dove Creek
POINT
BUG POINT
UTAH
COLORADO
G1
Cahone
CROSS CANYON
491
Pleasant View
Yellow Jacket
SANDSTONE CANYON
6057 ft
Lewis
CANYON
0
2.5
5
10
Km

G2

H1


F2
G1
G3
H2
G2
SPRING CREEK BASIN
SAN MIGUEL
Disappointment Creek
9271 ft
DOLORES
MONTEZUMA
Plateau Creek
STONER MESA
TAYLOR
HAYCAMP MESA
Lost Canyon Creek
184
Dolores
Km
0
2.5
5
10

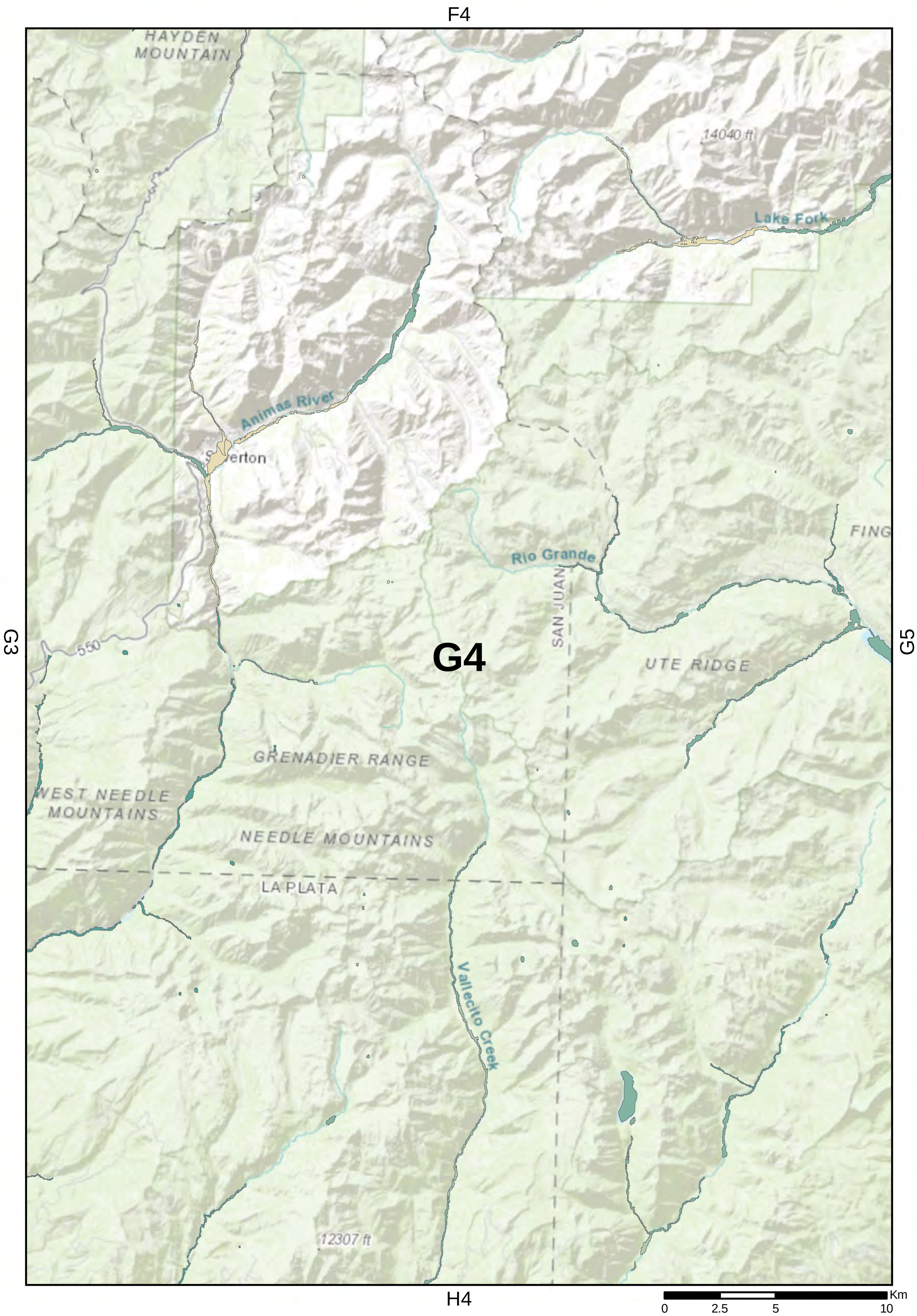
F3

G2

G4

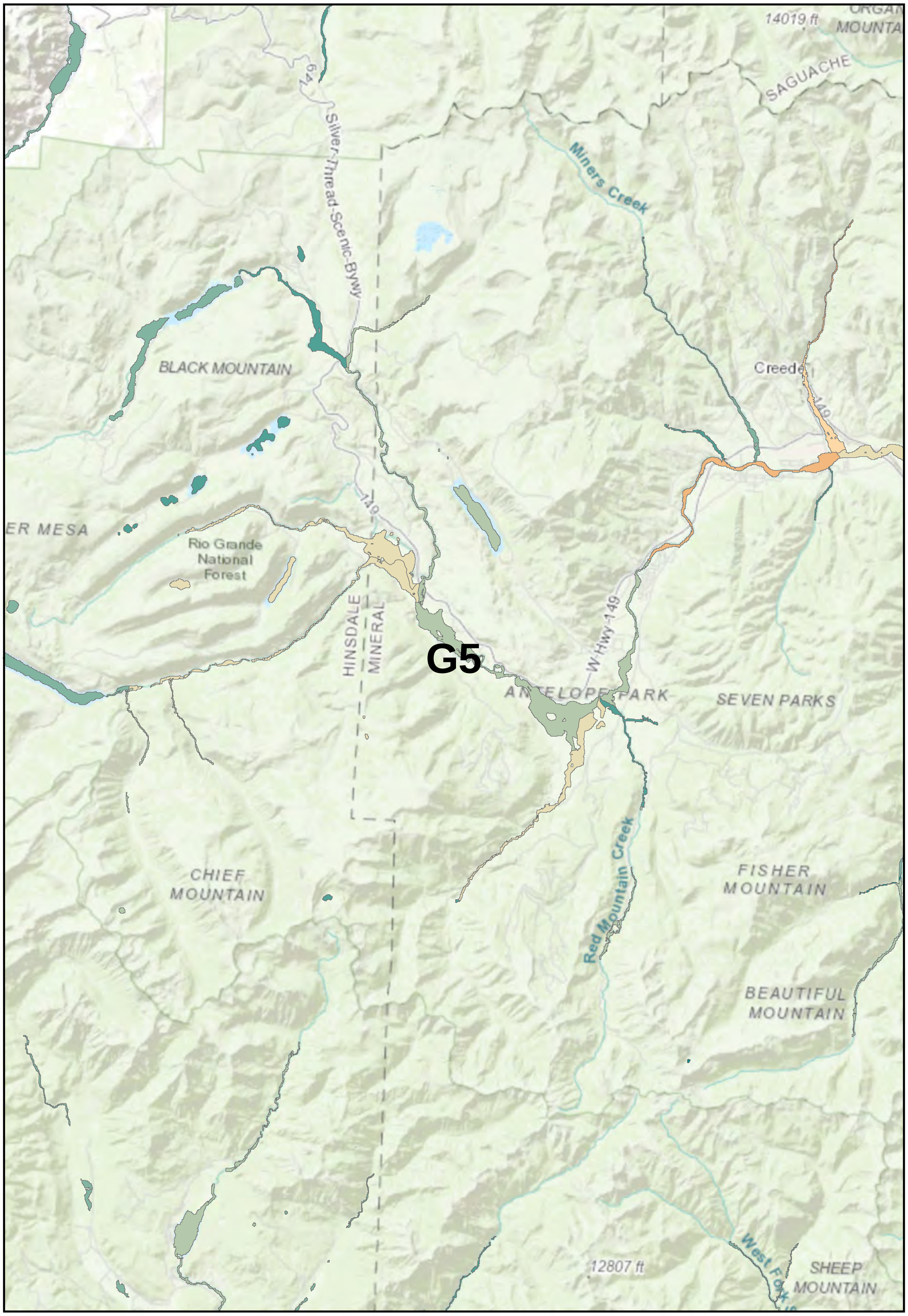
H3

0 2.5 5 10 Km


F4
HAYDEN MOUNTAIN
14040 ft
Lake Fork
Animas River
Silverton
FING
Rio Grande
SAN JUAN
G3
550
G4
UTE RIDGE
G5
GRENADIER RANGE
WEST NEEDLE MOUNTAINS
NEEDLE MOUNTAINS
LA PLATA
Vallecito Creek
12307 ft
H4
0
2.5
5
10
Km

F5

G4



G6

H5

0 2.5 5 10 Km

F6

G5

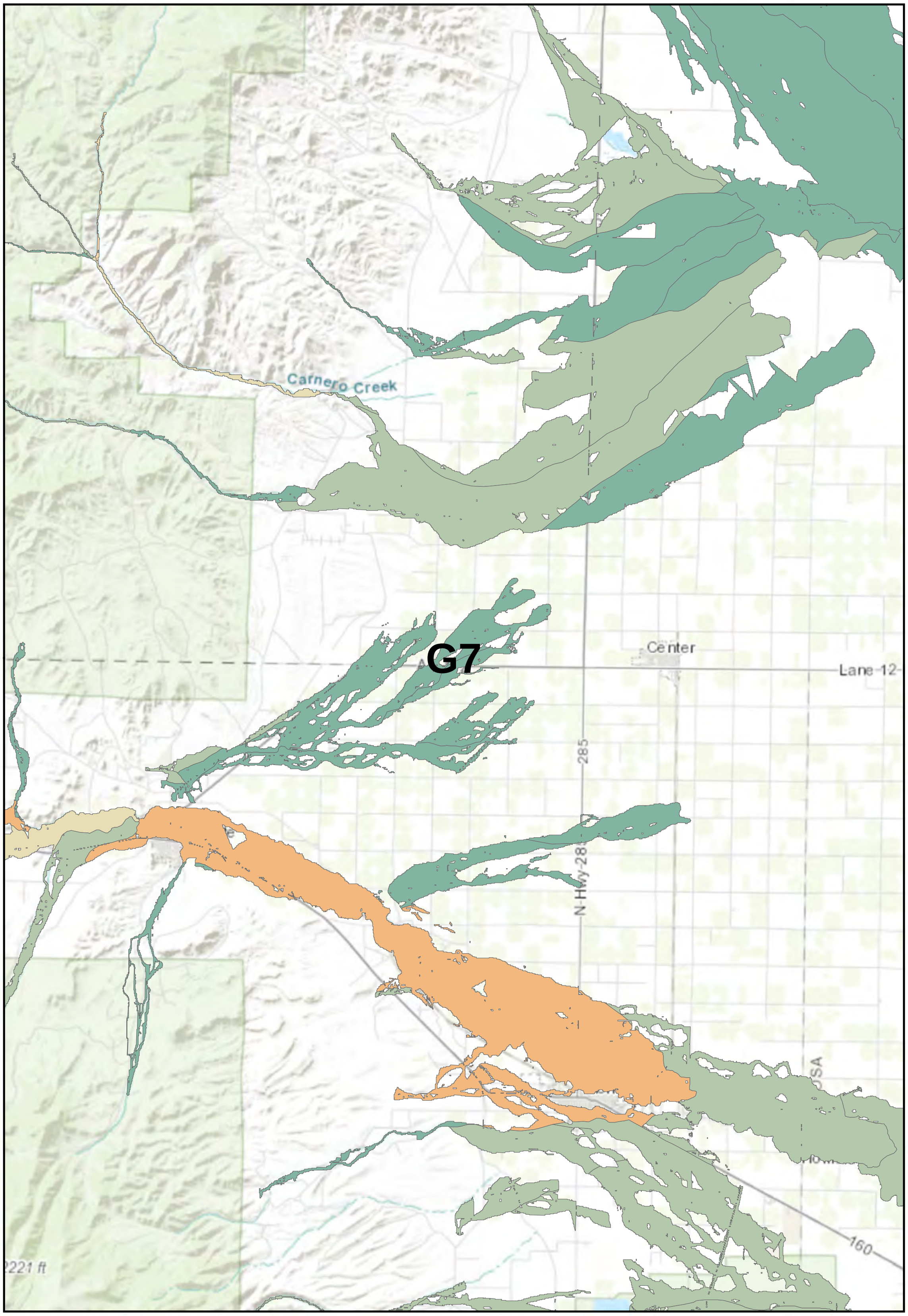
G7

H6

0 2.5 5 10 Km

F7

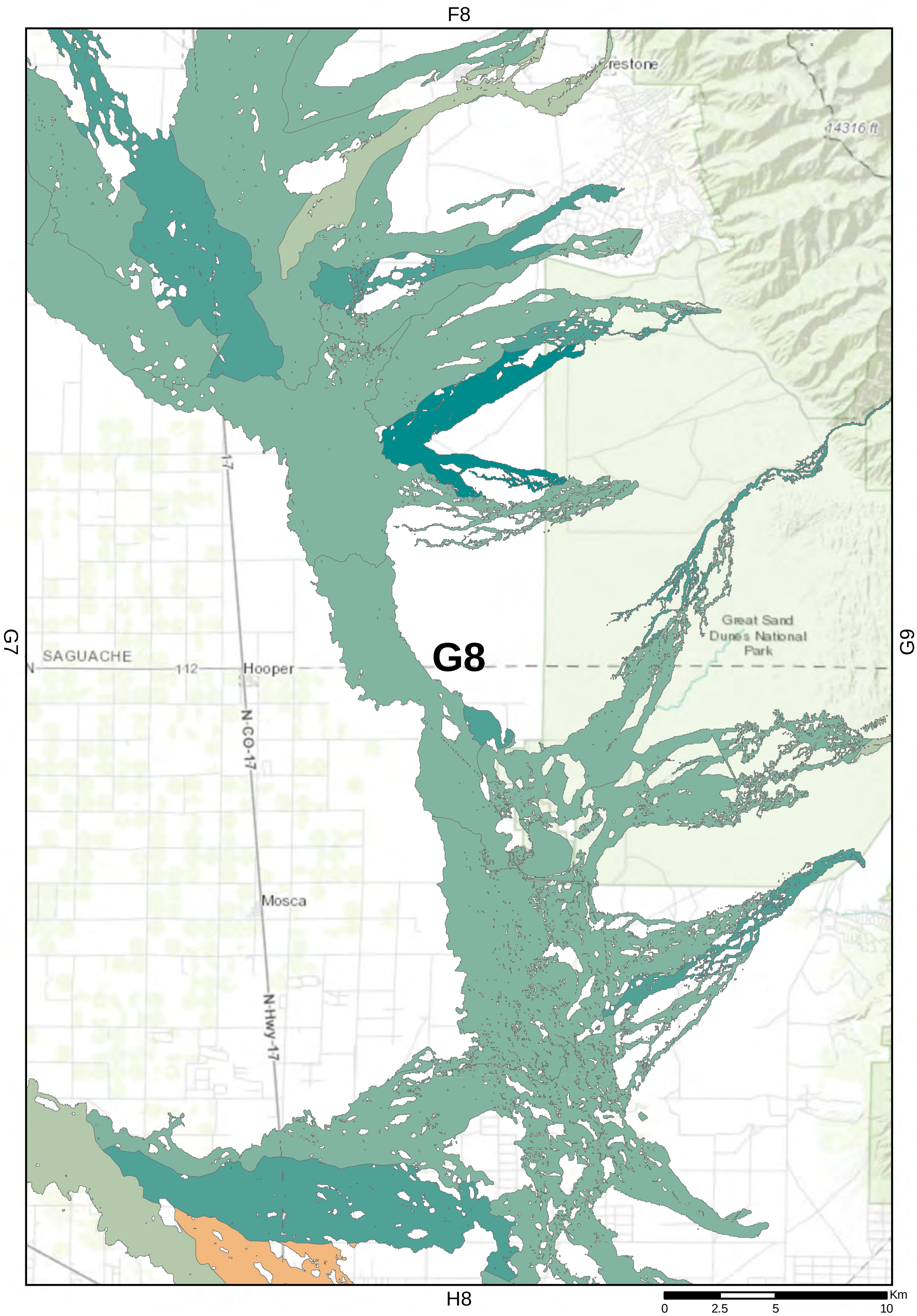
G6



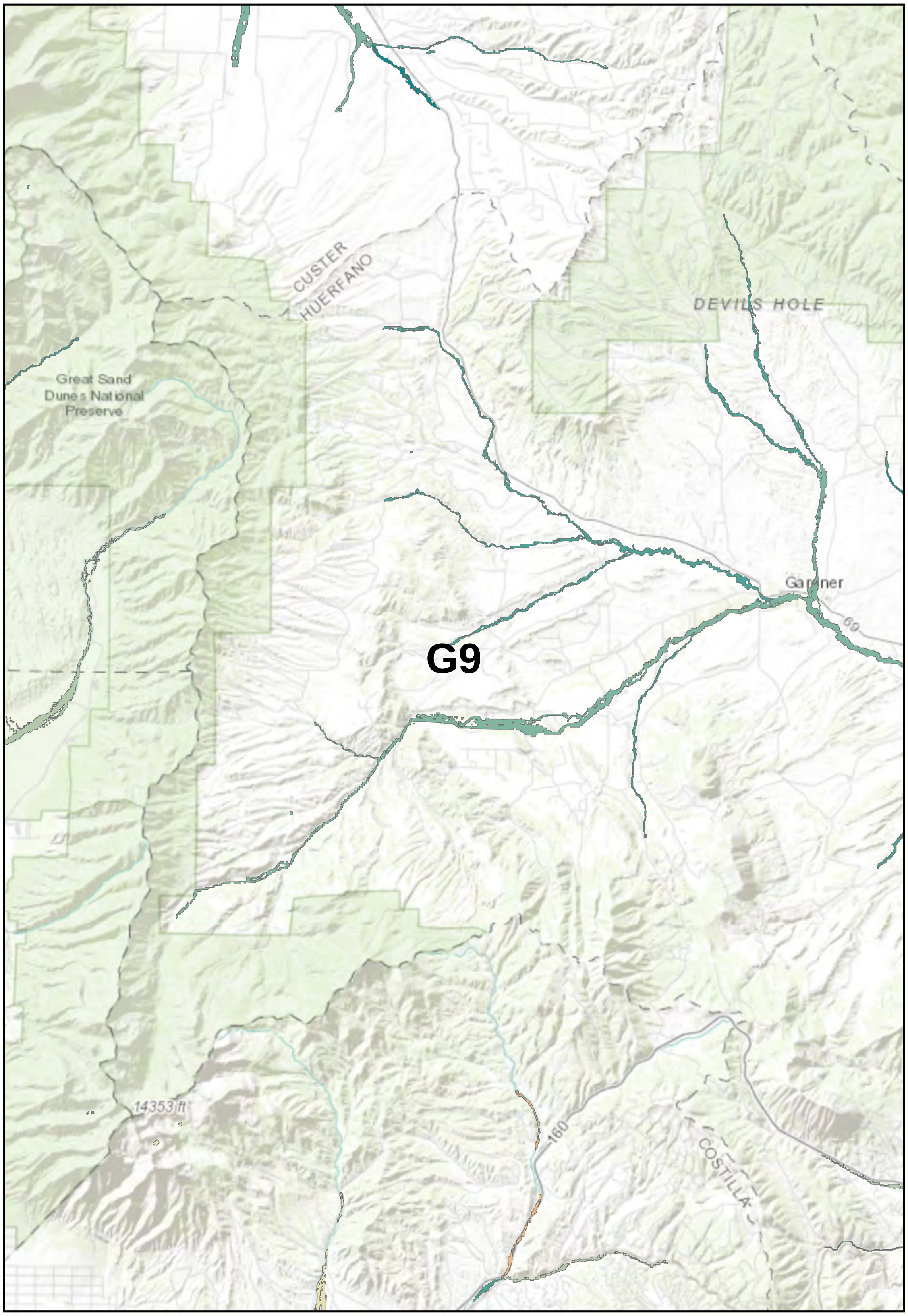
G8

H7

0 2.5 5 10 Km


F8
Crestone
14316 ft
Great Sand Dunes National Park
G7
SAGUACHE
112
Hooper
G8
G9
17
N-CO-17
Mosca
N-Hwy-17
H8
0
2.5
5
10
Km

F9



G8

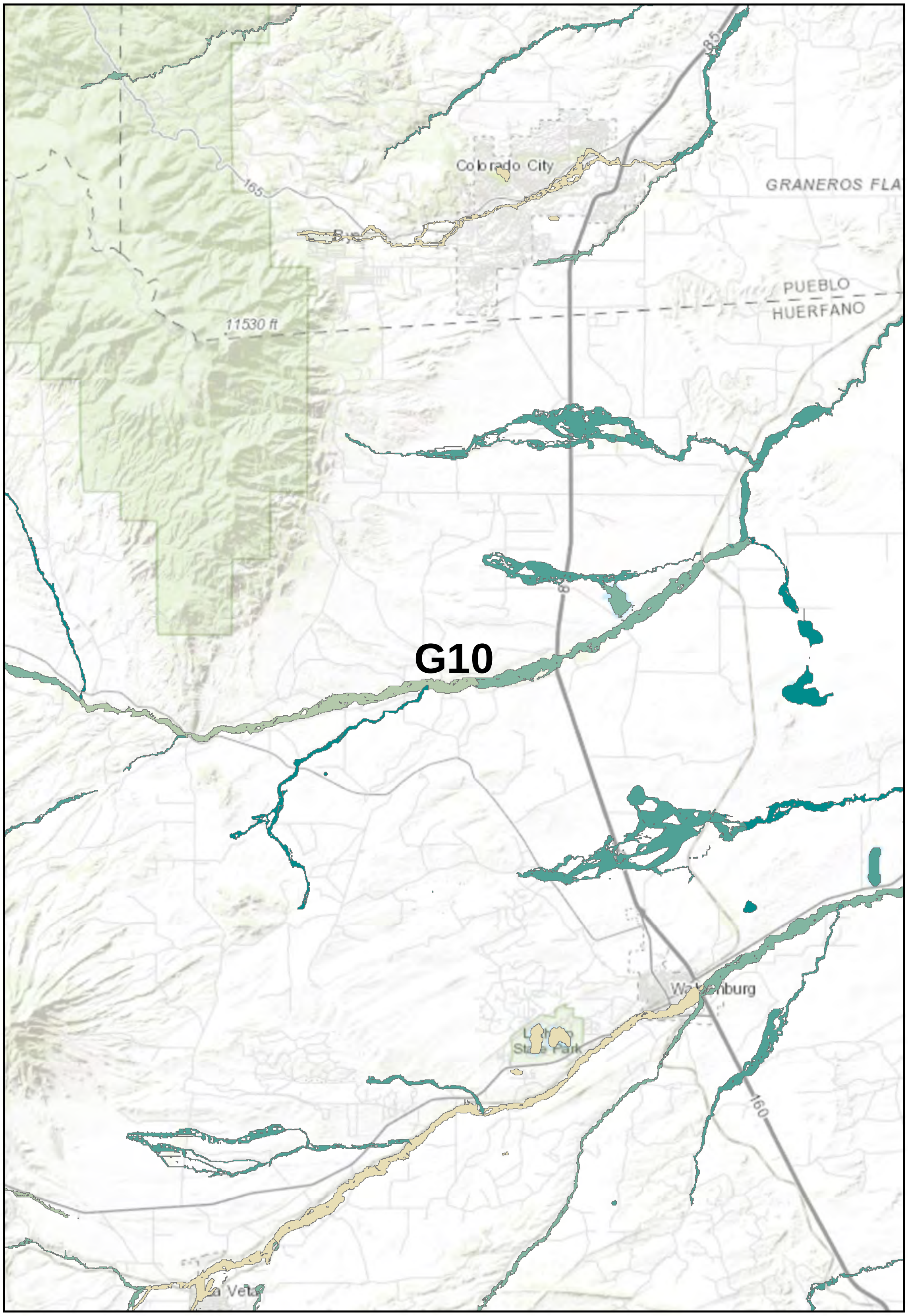
G10

H9

0 2.5 5 10 Km

F10

G9



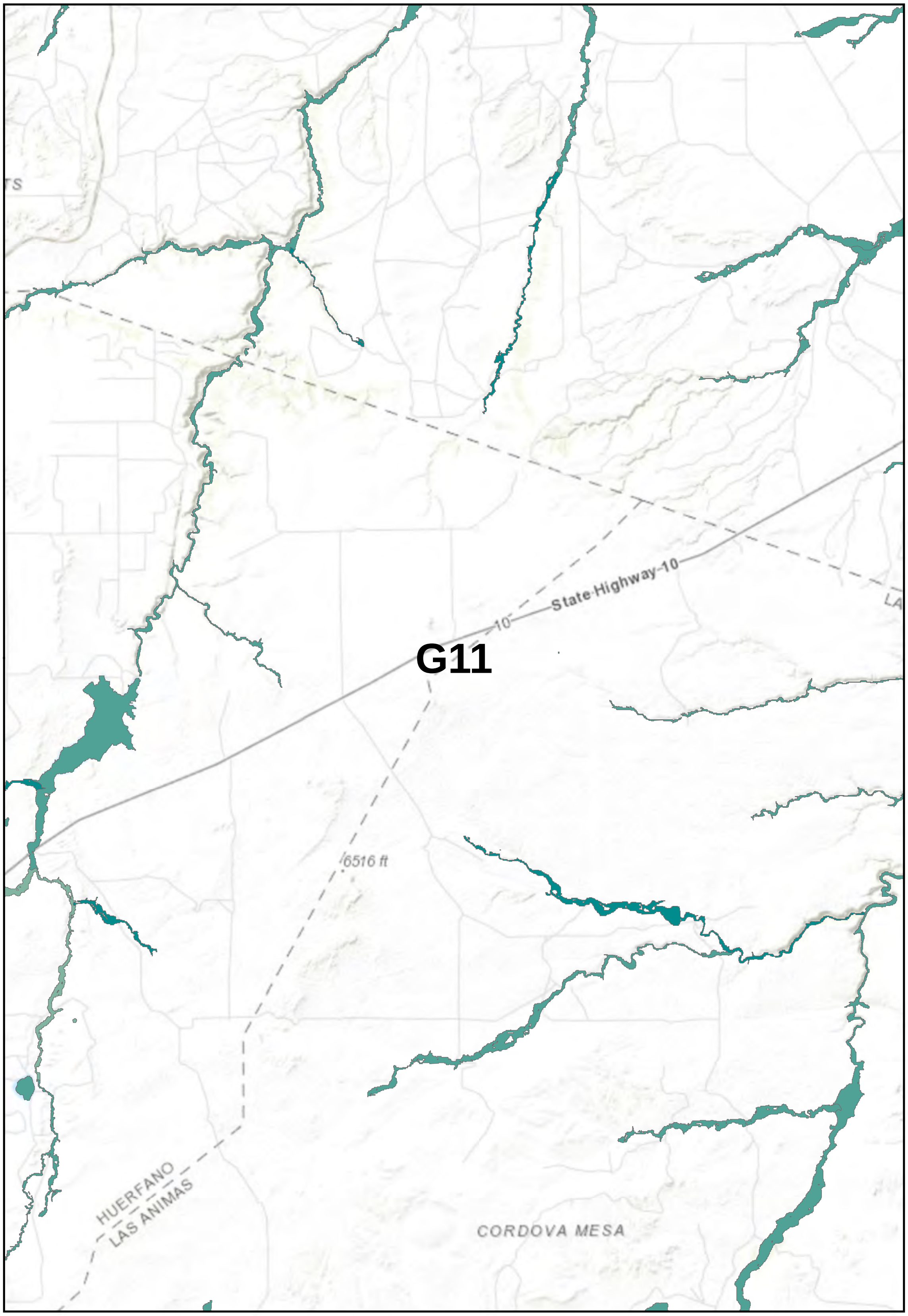
G11

H10

0 2.5 5 10 Km

F11

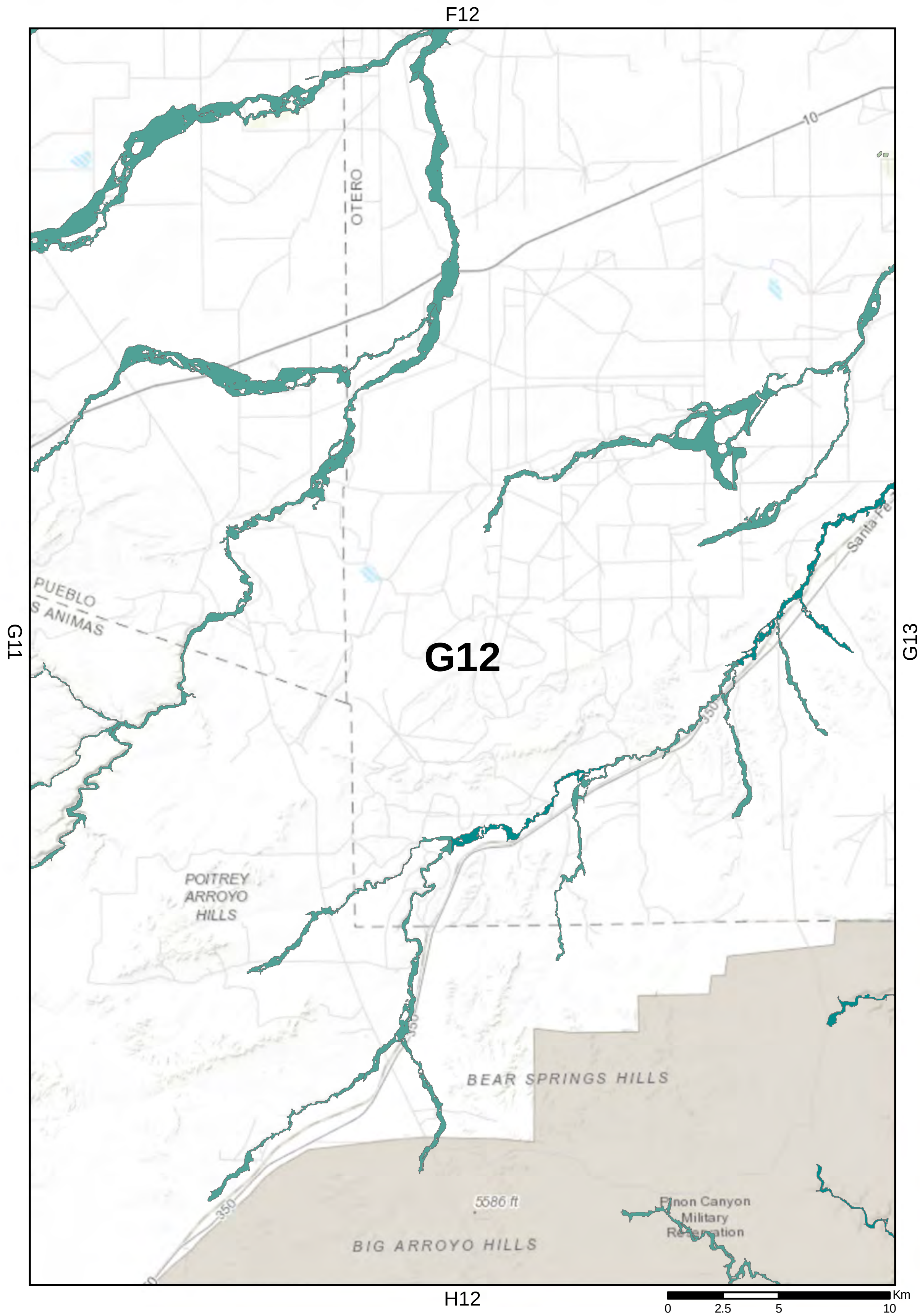
G10



G12

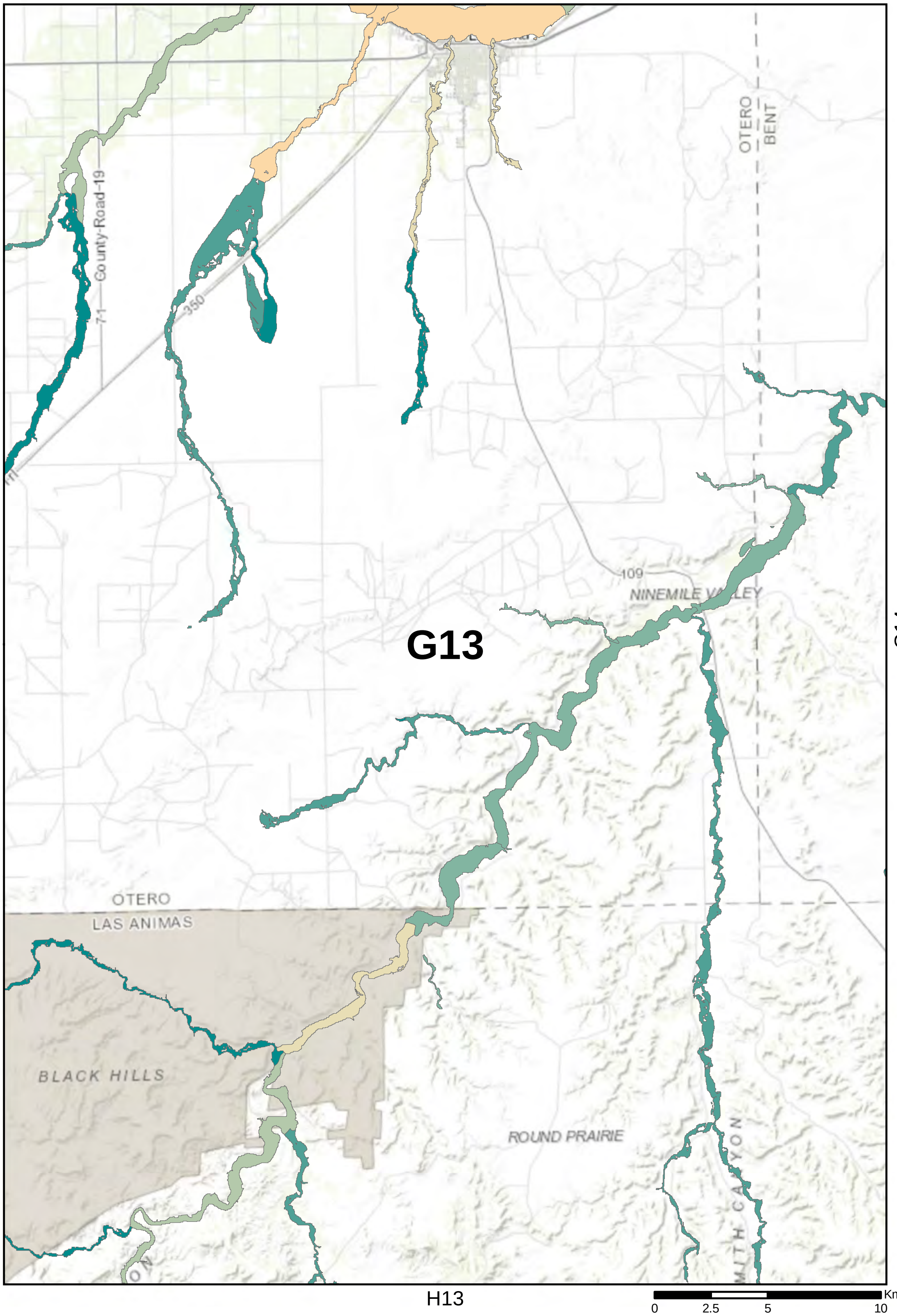
H11

0 2.5 5 10 Km


F12
G11
G12
G13
H12
OTERO
PUEBLO
S ANIMAS
10
Santa Fe
350
POITREY
ARROYO
HILLS
BEAR SPRINGS HILLS
5586 ft
Pinon Canyon
Military
Reservation
BIG ARROYO HILLS
Km
0
2.5
5
10

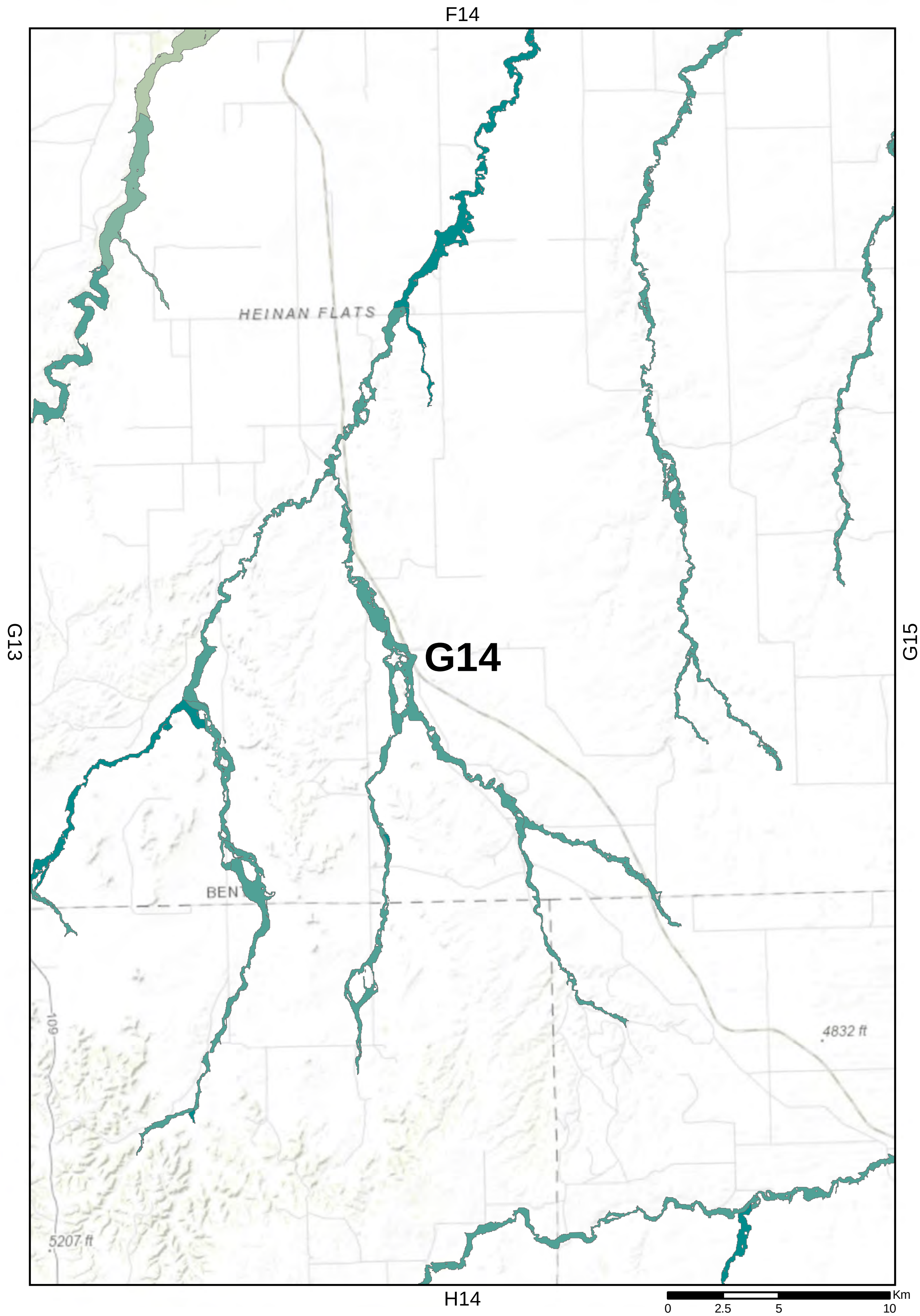
F13

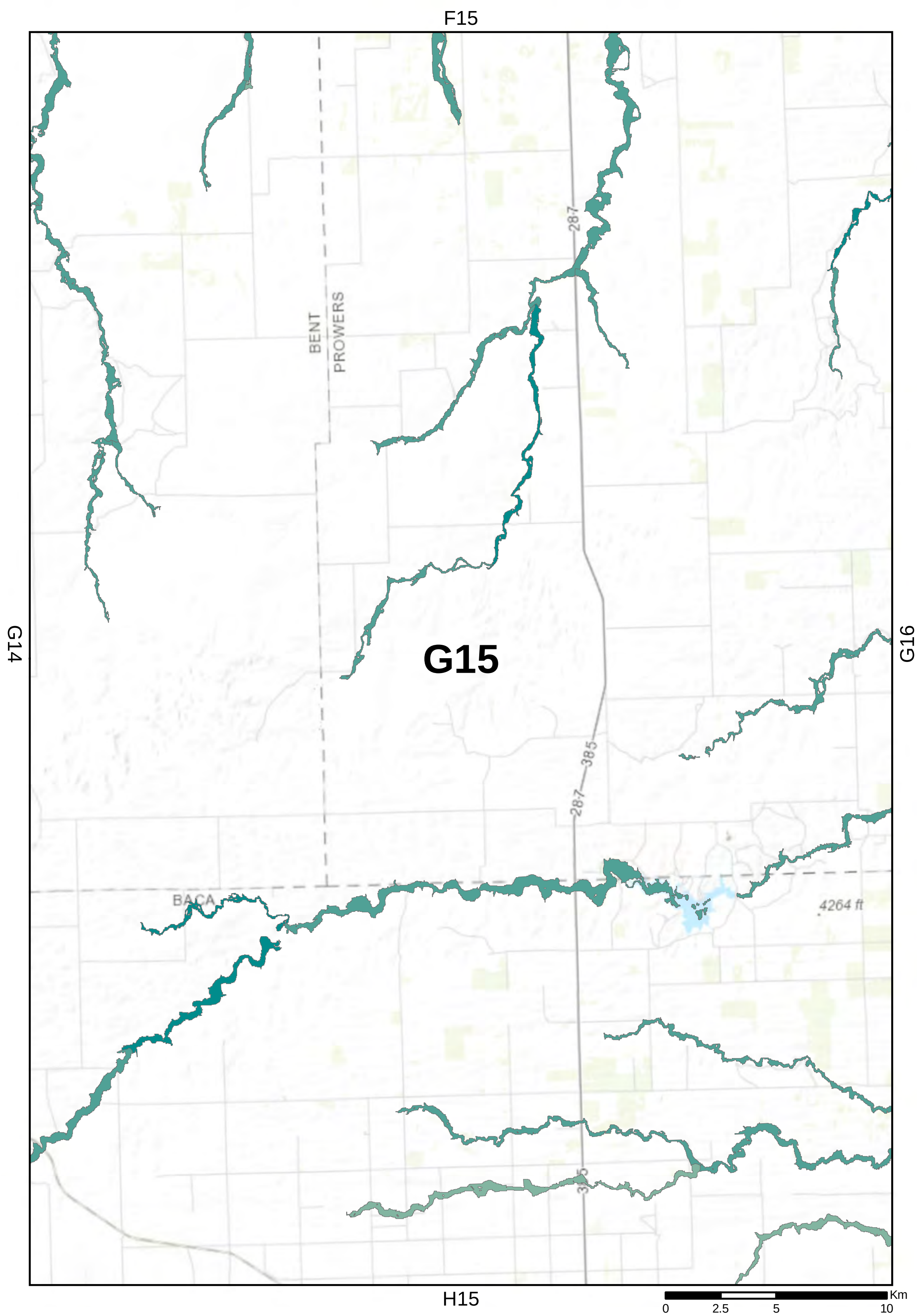
G12



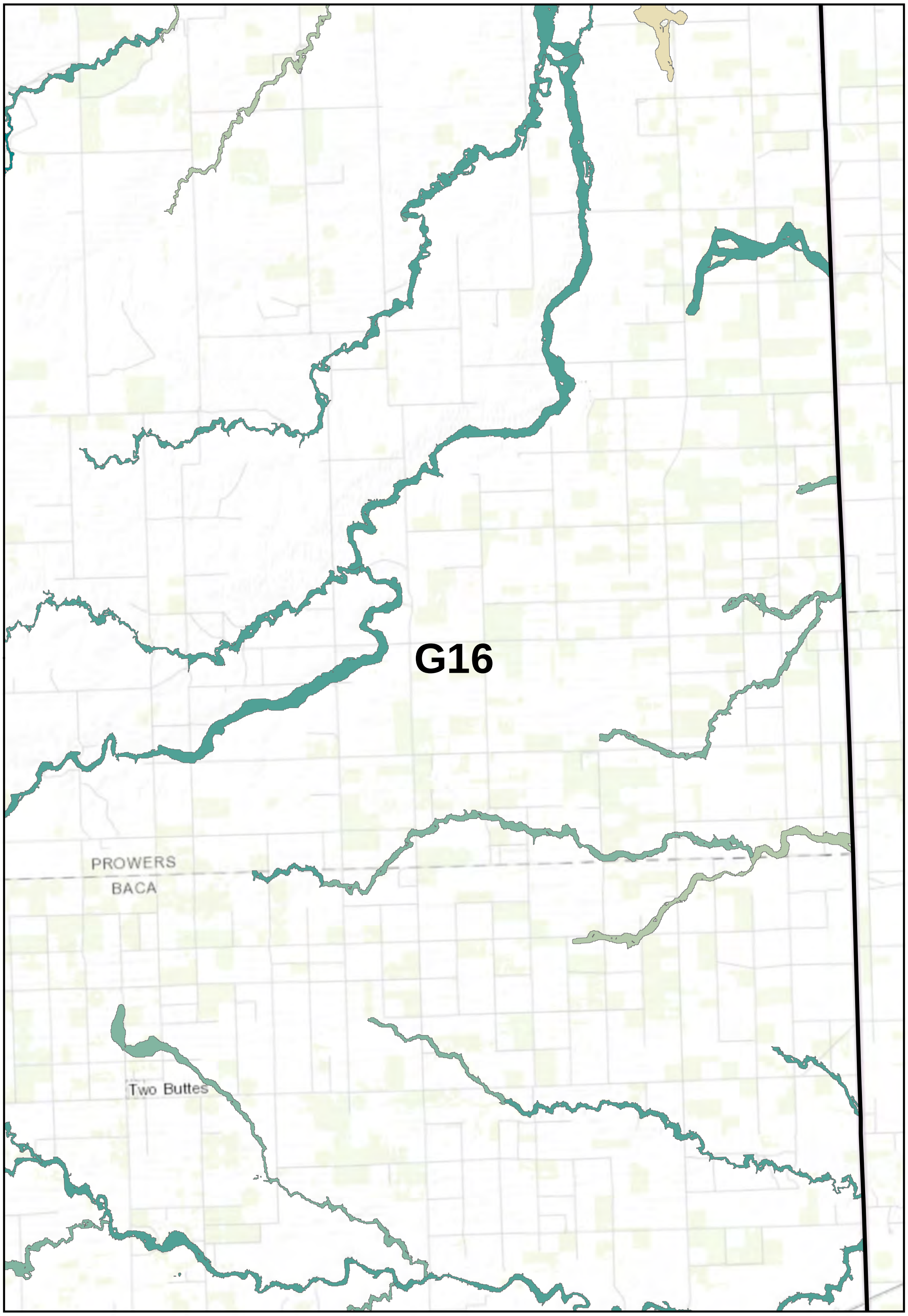
G14

H13


F14
G13
G15
H14
G14
HEINAN FLATS
BEN
109
5207 ft
4832 ft
Km
0
2.5
5
10


F15
G14
G16
H15
G15
BENT
PROWERS
BACA
287
385
4264 ft
0
2.5
5
10
Km

F16

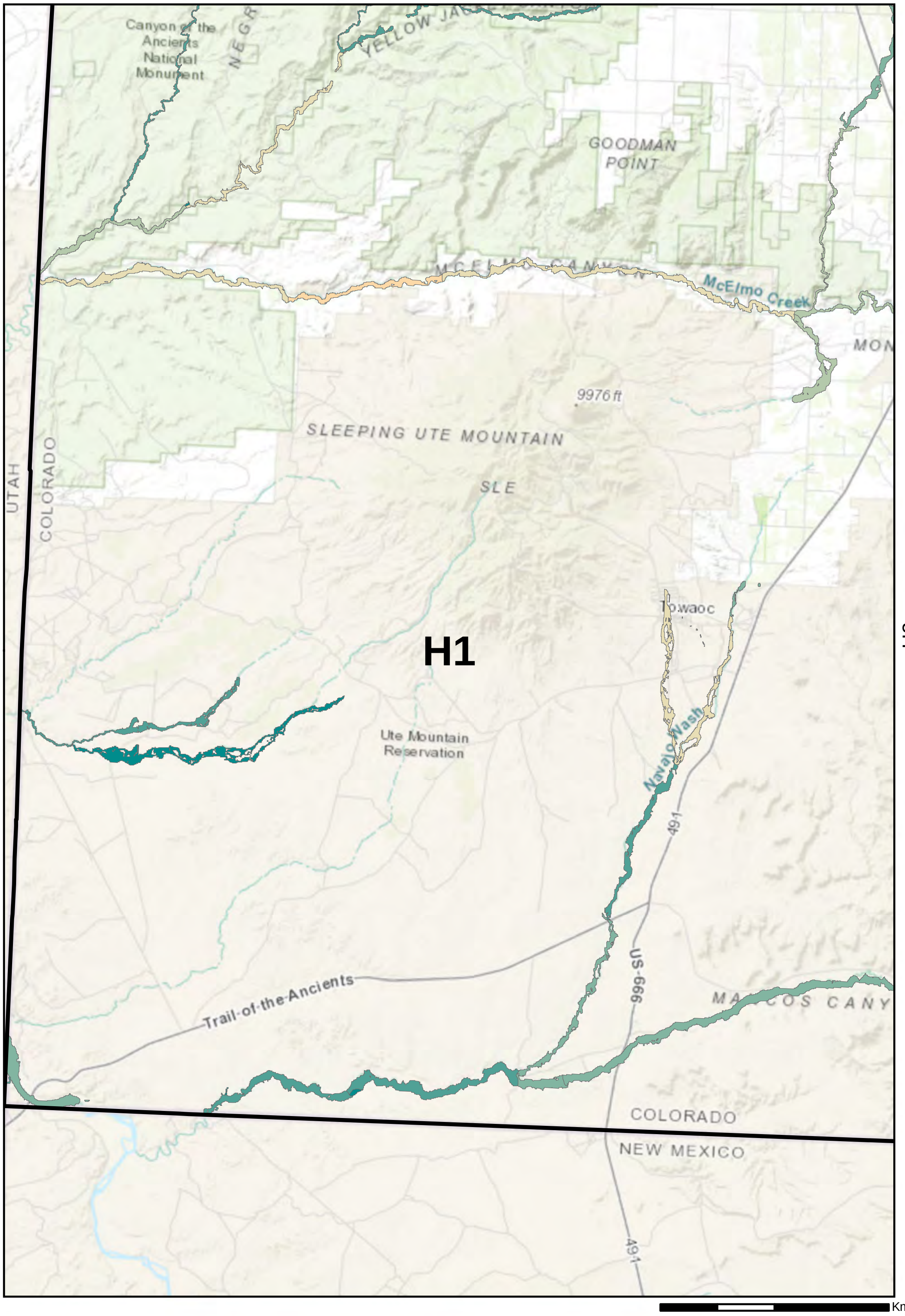


G15

H16

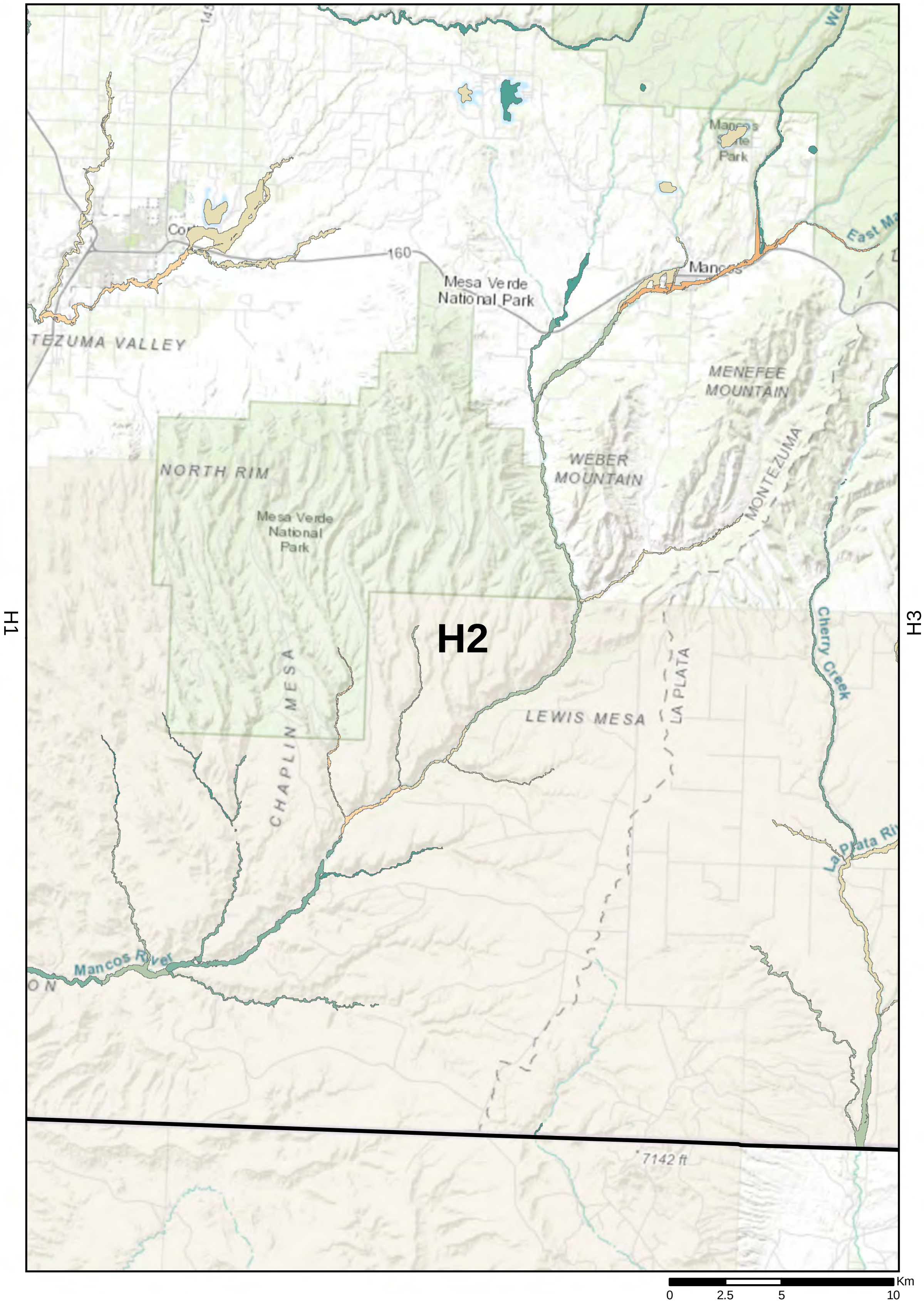
0 2.5 5 10 Km

G1

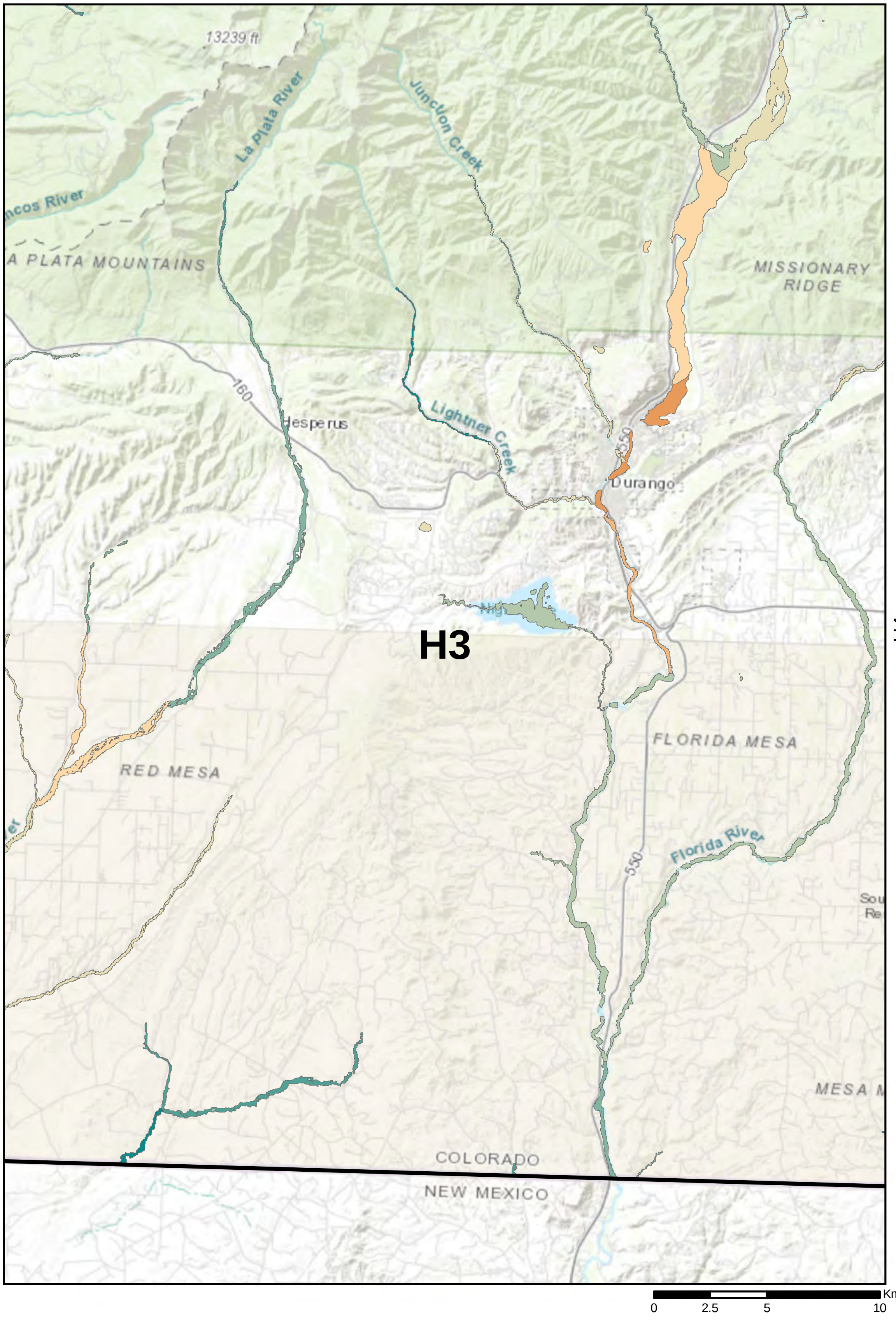

Canyon of the Ancients National Monument
YELLOW JA
GOODMAN POINT
McElmo Creek
MON
9976 ft
SLEEPING UTE MOUNTAIN
SLE
UTAH
COLORADO
Towaoc
H1
Ute Mountain Reservation
Navajo Wash
491
US-666
Trail-of-the-Ancients
COLORADO
NEW MEXICO
491
0 2.5 5 10 Km

H2

G2


H2
H1
H3
Mesa Verde National Park
Mesa Verde National Park
NORTH RIM
TEZUMA VALLEY
MENEFEE MOUNTAIN
WEBER MOUNTAIN
MONTEZUMA
LEWIS MESA
LA PLATA
CHAPLIN MESA
Mancos River
Cherry Creek
La Plata Ri
Mancos
Mancos State Park
160
7142 ft
Km
0
2.5
5
10

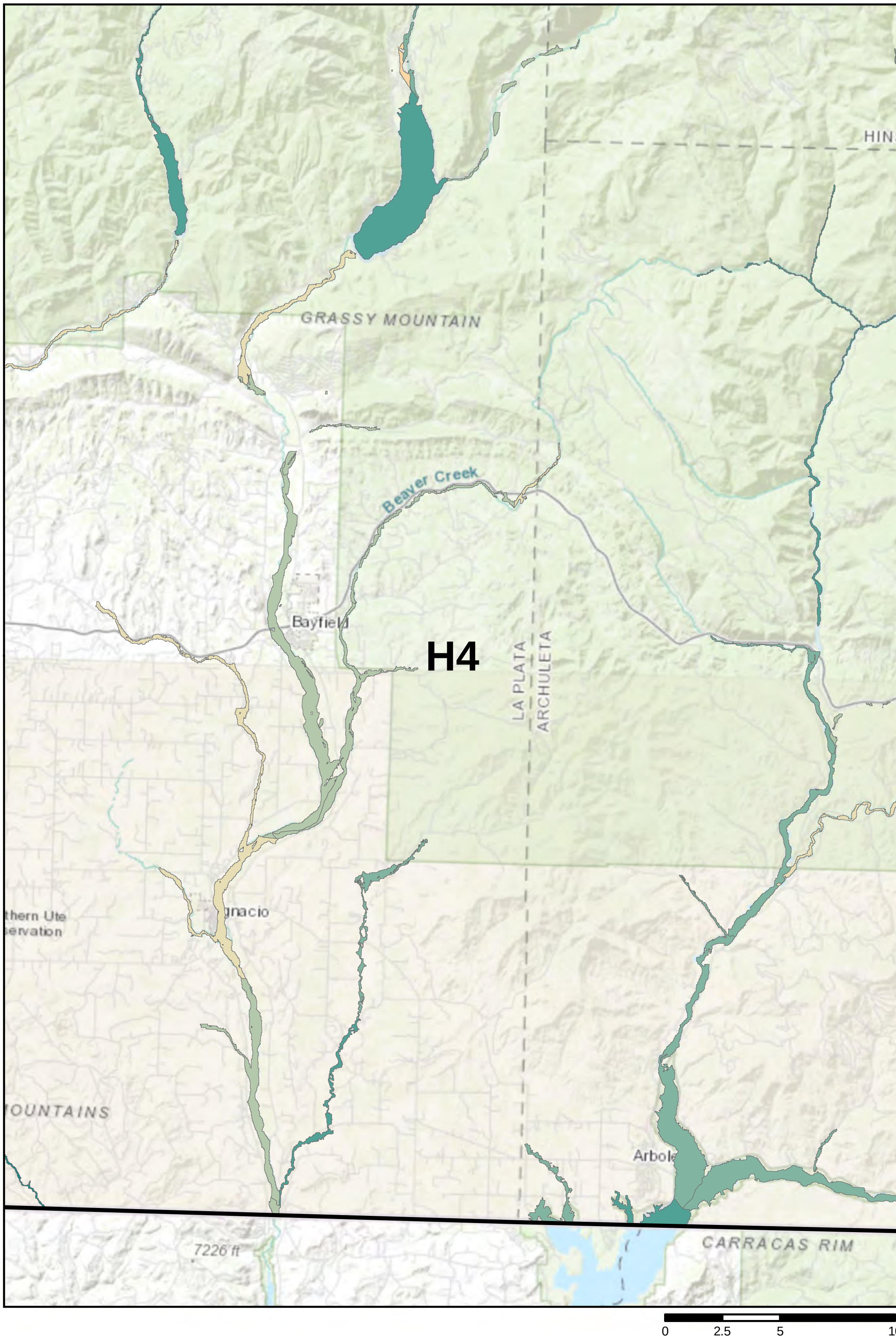
G3


13239 ft
La Plata River
Junction Creek
ncos River
A PLATA MOUNTAINS
MISSIONARY RIDGE
160
Hesperus
Lightner Creek
550
Durango
H3
FLORIDA MESA
RED MESA
Florida River
550
MESA M
COLORADO
NEW MEXICO
0 2.5 5 10 Km

H2

H4

G4

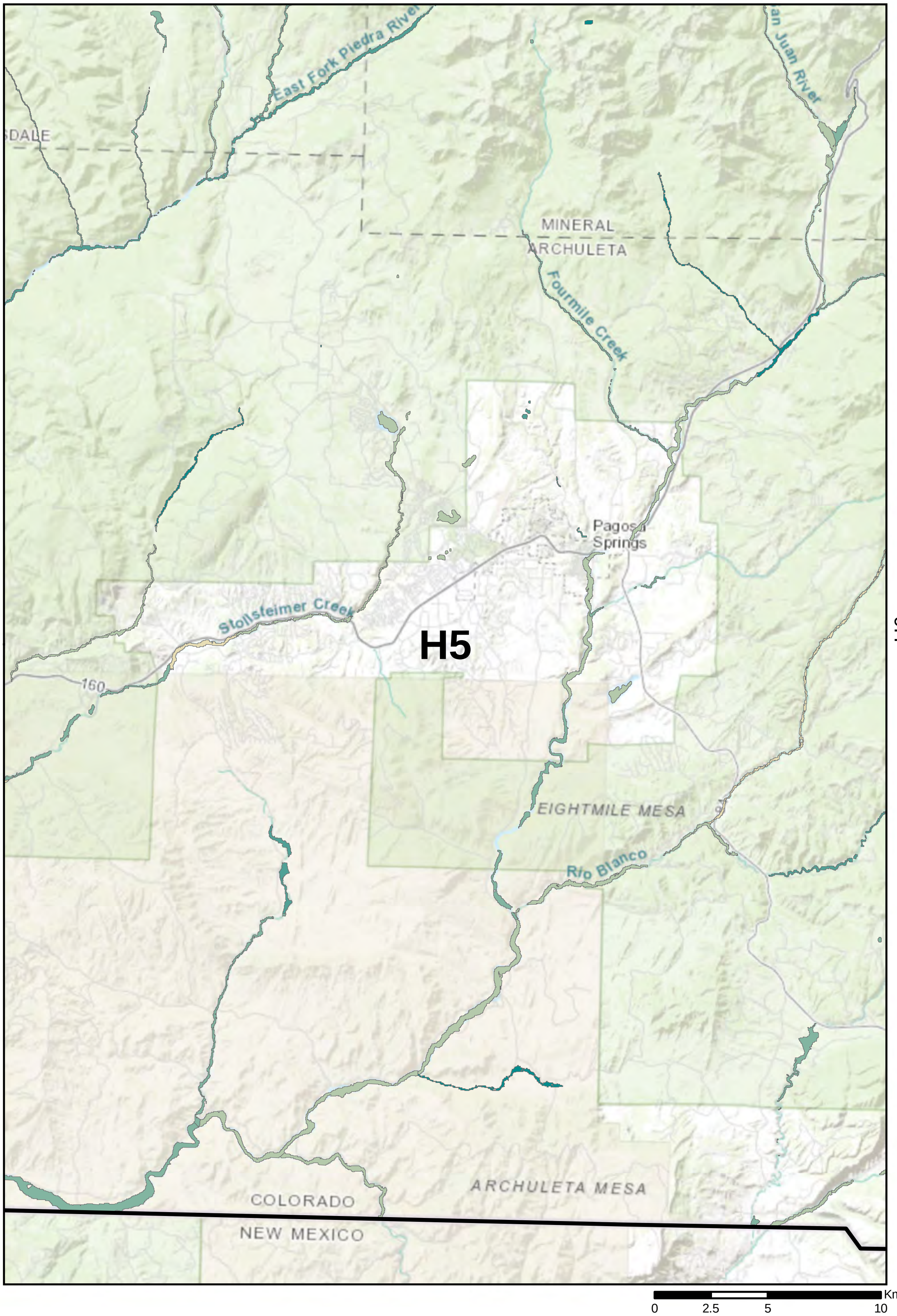

HINS
GRASSY MOUNTAIN
Beaver Creek
Bayfield
H4
LA PLATA
ARCHULETA
thern Ute
ervation
gnacio
OUNTAINS
Arbol
7226 ft
CARRACAS RIM
Km
0
2.5
5
10

H3

H5

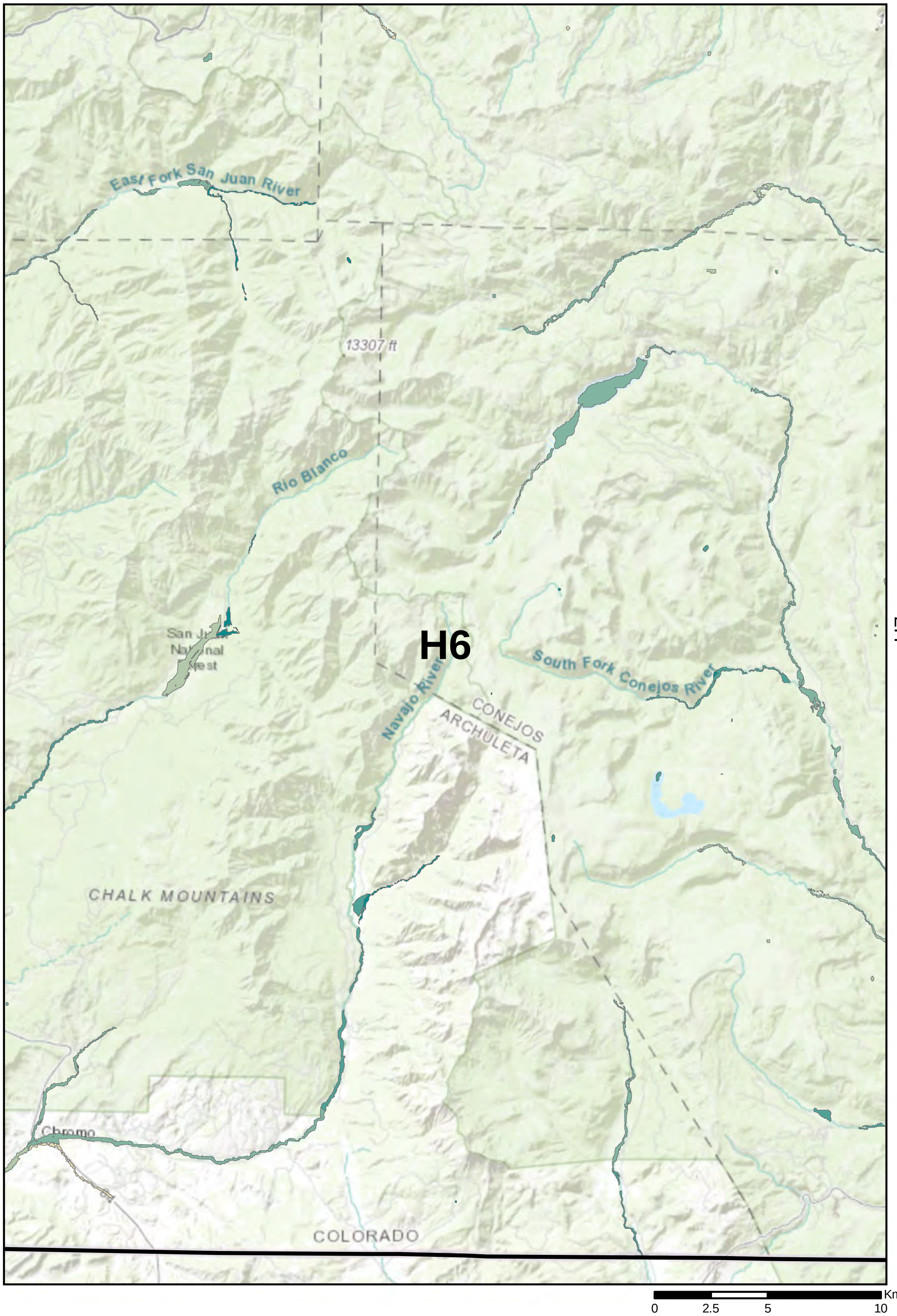
G5

H4


East Fork Piedra River
San Juan River
SDALE
MINERAL
ARCHULETA
Fourmile Creek
Pagosa Springs
Stollsteimer Creek
160
H5
EIGHTMILE MESA
Rio Blanco
ARCHULETA MESA
COLORADO
NEW MEXICO
Km
0
2.5
5
10

H6

G6

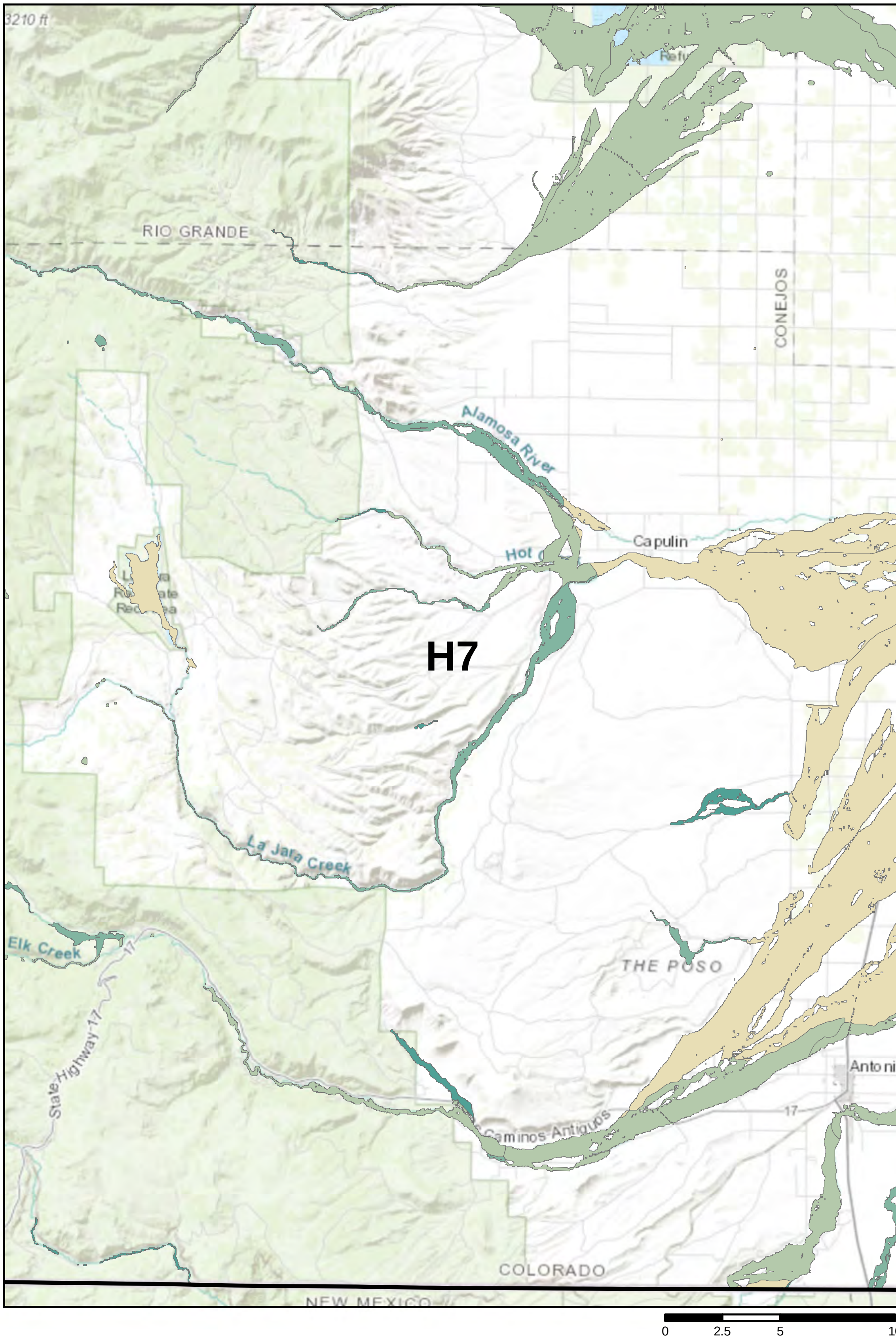

East Fork San Juan River
13307 ft
Rio Blanco
San Juan National Forest
H6
South Fork Conejos River
Navajo River
CONEJOS
ARCHULETA
CHALK MOUNTAINS
Chromo
COLORADO
Km
0
2.5
5
10

H5

H7

G7

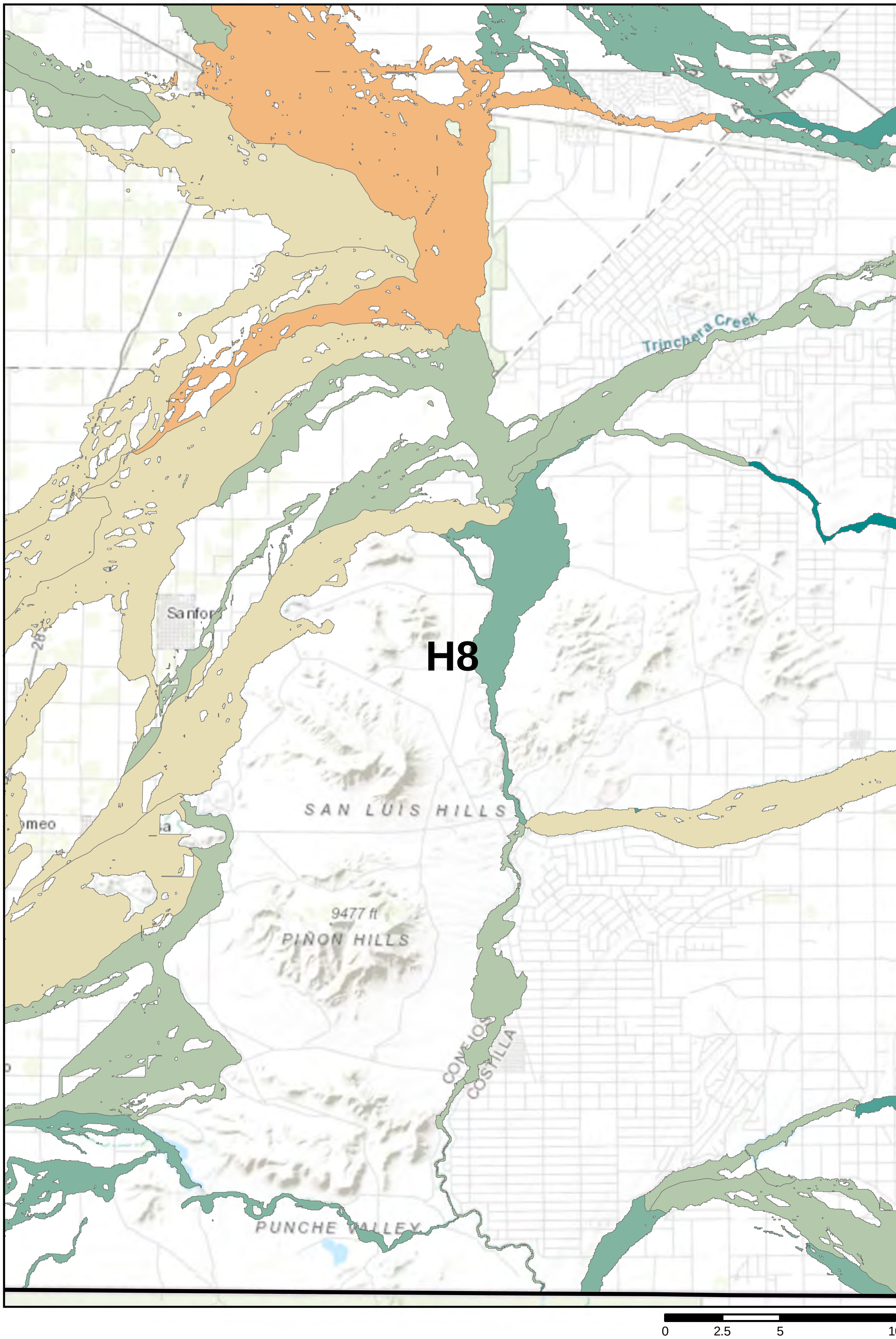
H6



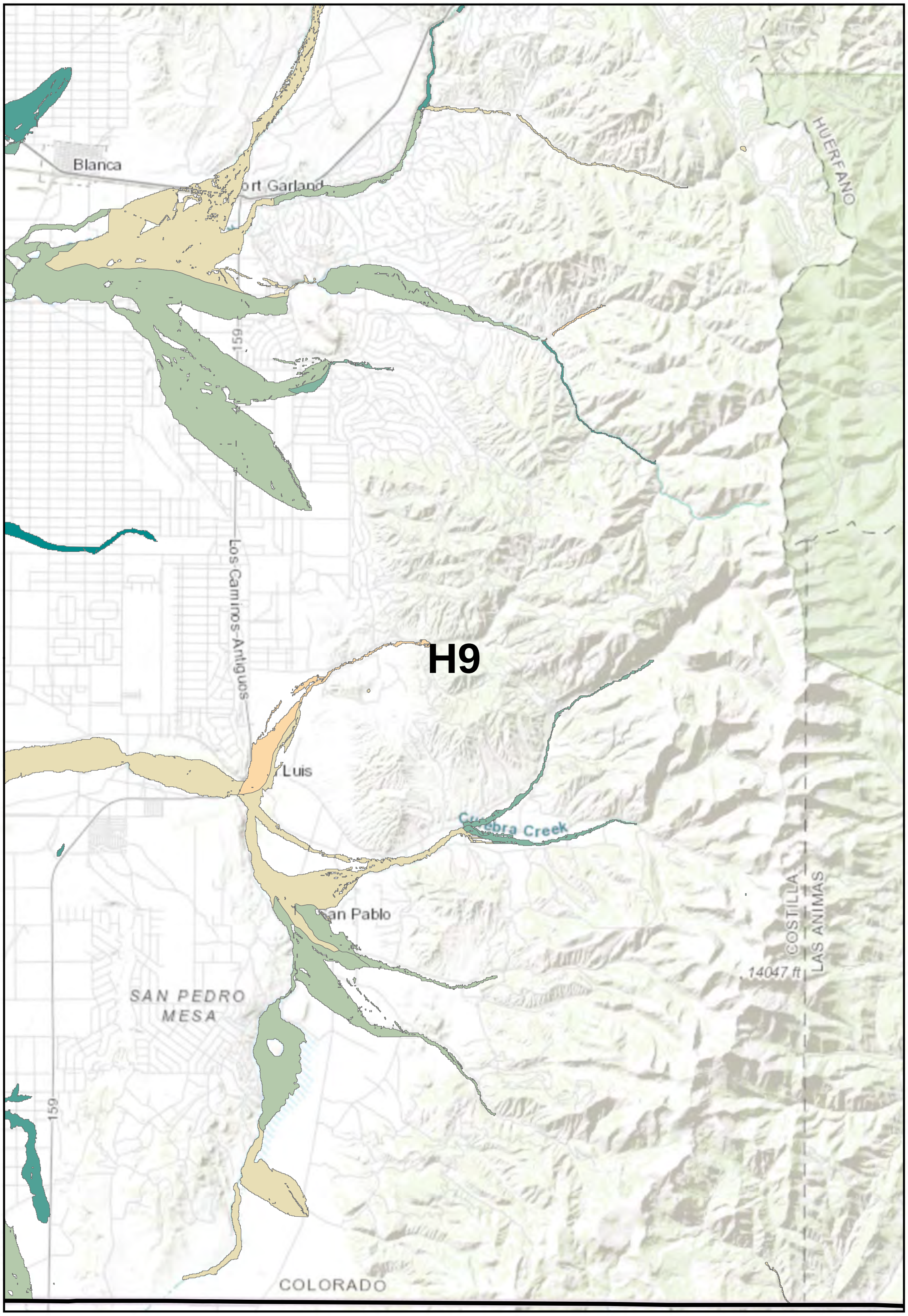
RIO GRANDE
CONEJOS
Alamosa River
Capulin
Hot
H7
La Jara Creek
Elk Creek
State Highway 17
17
THE POSO
Caminos Antiguos
COLORADO
NEW MEXICO
0
2.5
5
10
Km

H8

G8

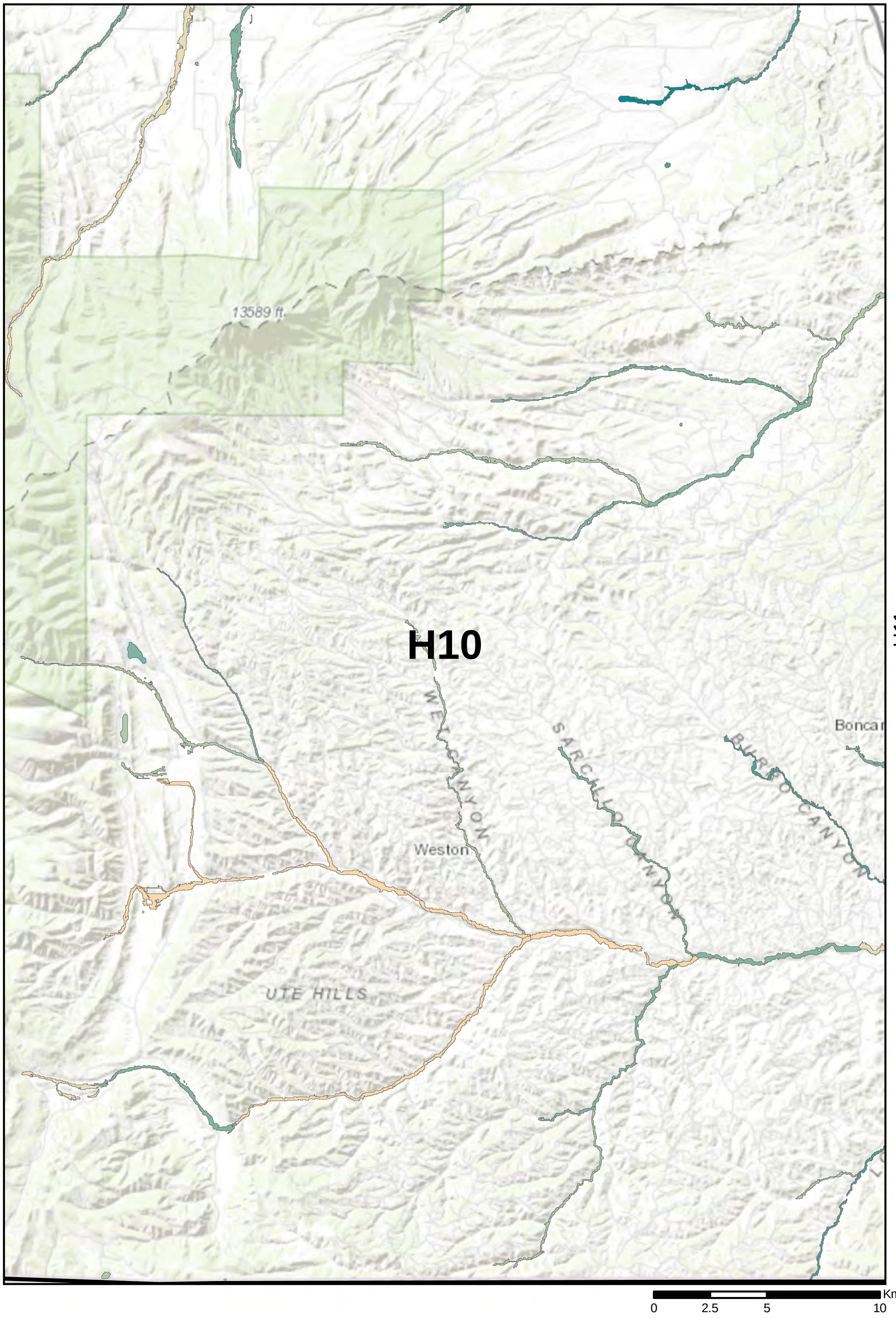

H7
H9
H8
Trinchera Creek
Sanford
SAN LUIS HILLS
9477 ft
PIÑON HILLS
CONEJOS
COSTILLA
PUNCHE VALLEY
Km
0
2.5
5
10

G9



H8
H10
H9
Blanca
Fort Garland
159
Los Caminos Antiguos
HUERFANO
Luis
San Pablo
Culebra Creek
SAN PEDRO MESA
COSTILLA
LAS ANIMAS
14047 ft
COLORADO
0
2.5
5
10
Km

G10



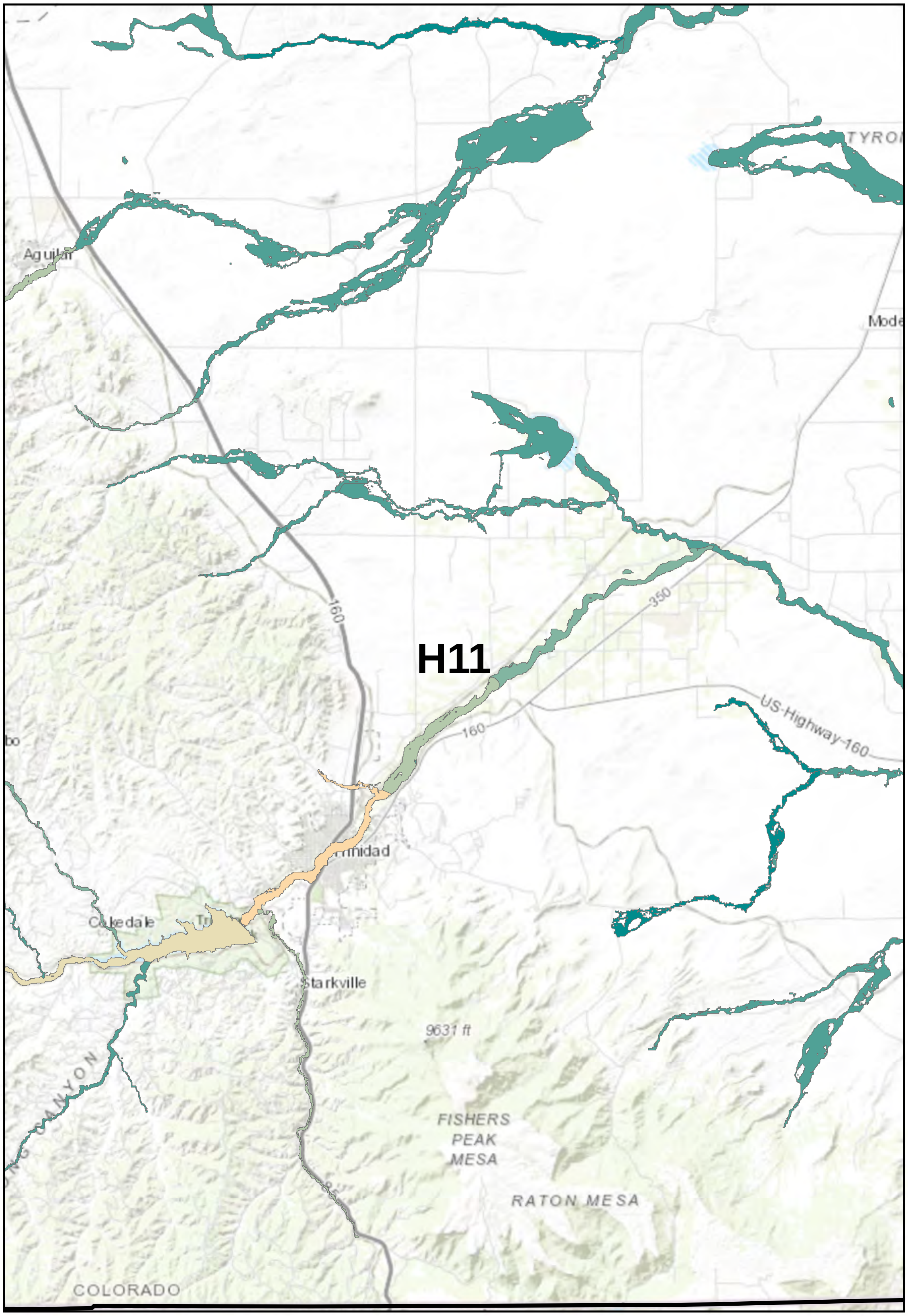
13589 ft.
H10
WET CANYON
SARCILLO CANYON
BURRO CANYON
Boncar
Weston
UTE HILLS
Km
0
2.5
5
10

H9

H11

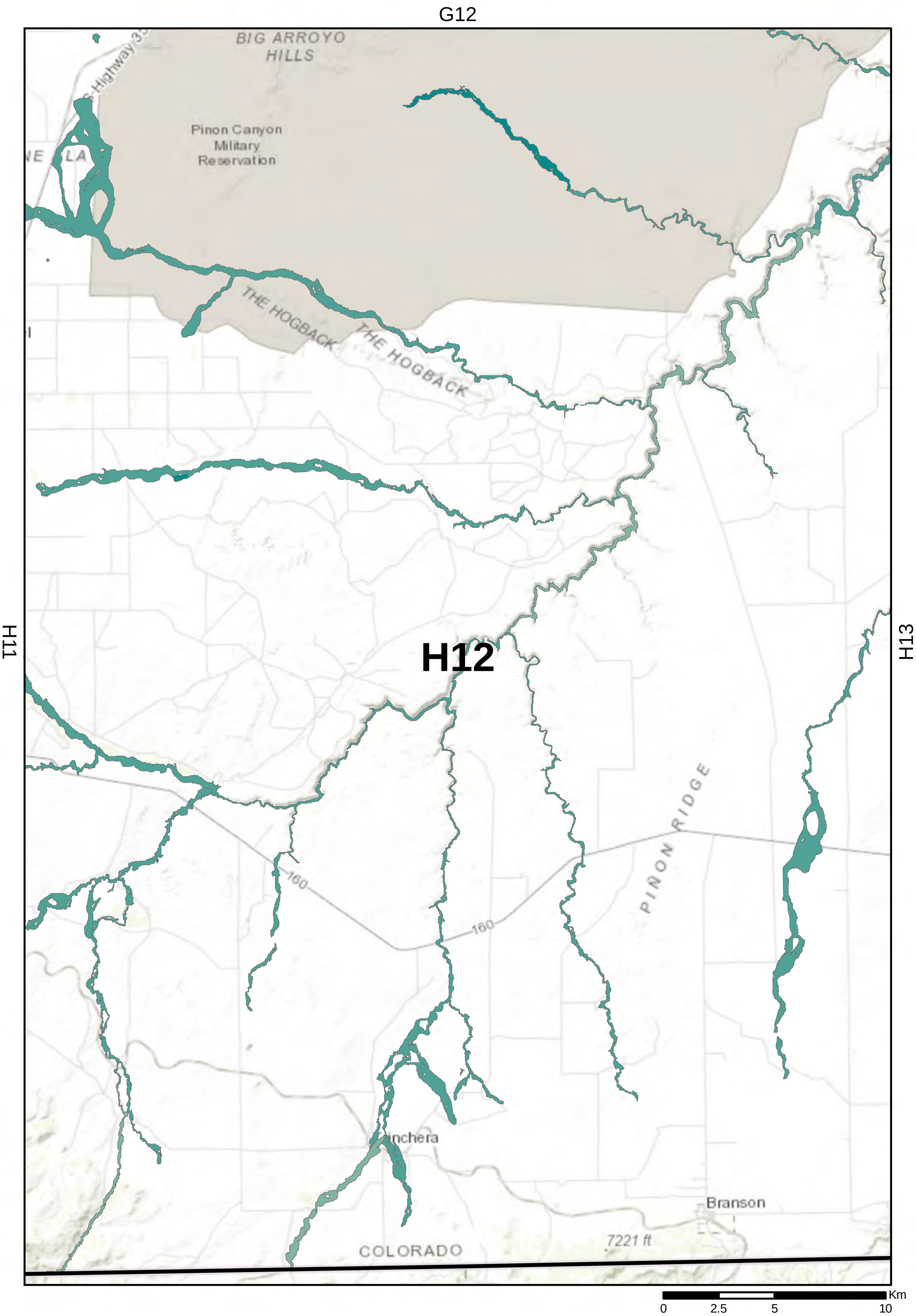
G11

H10

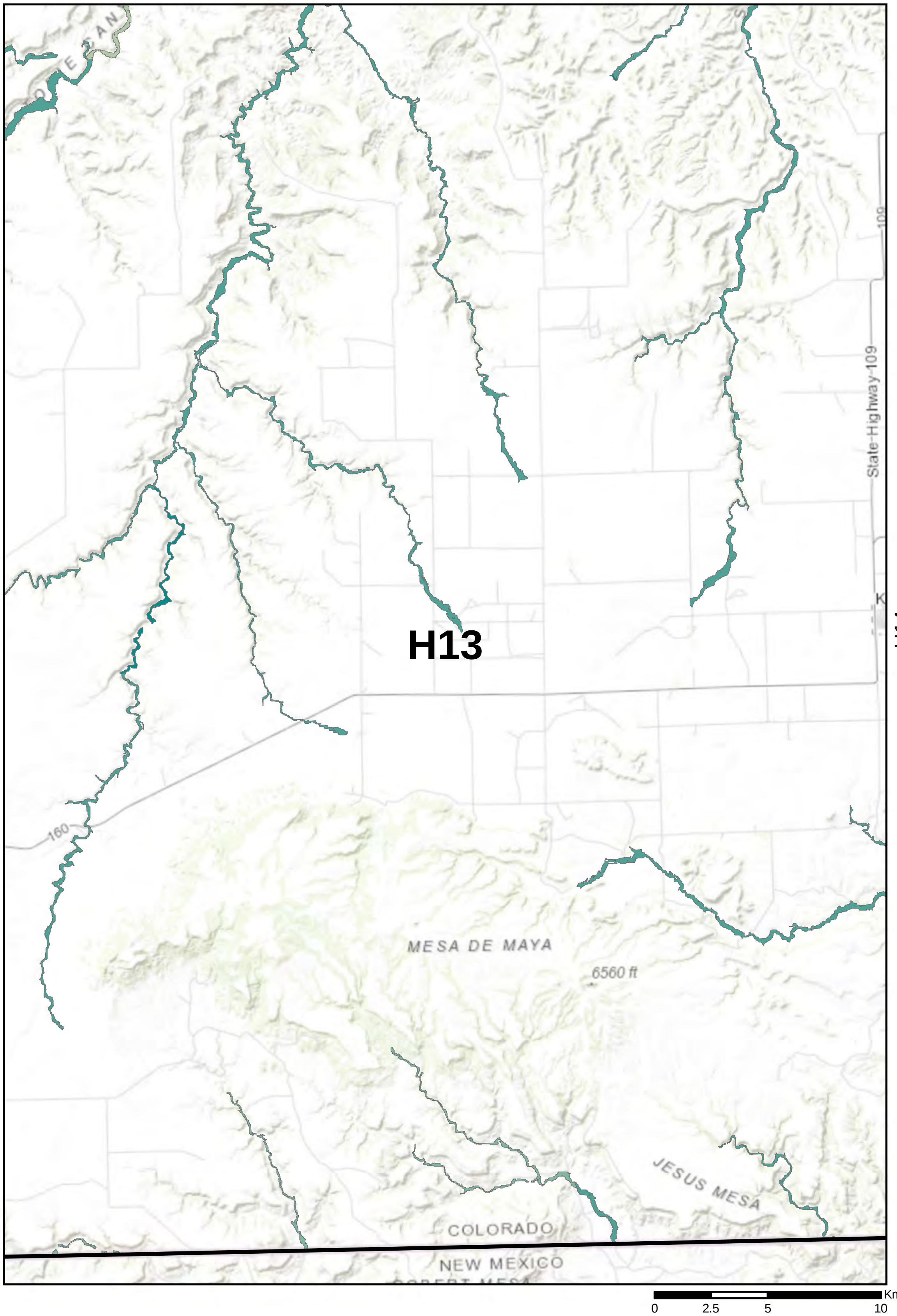


H12

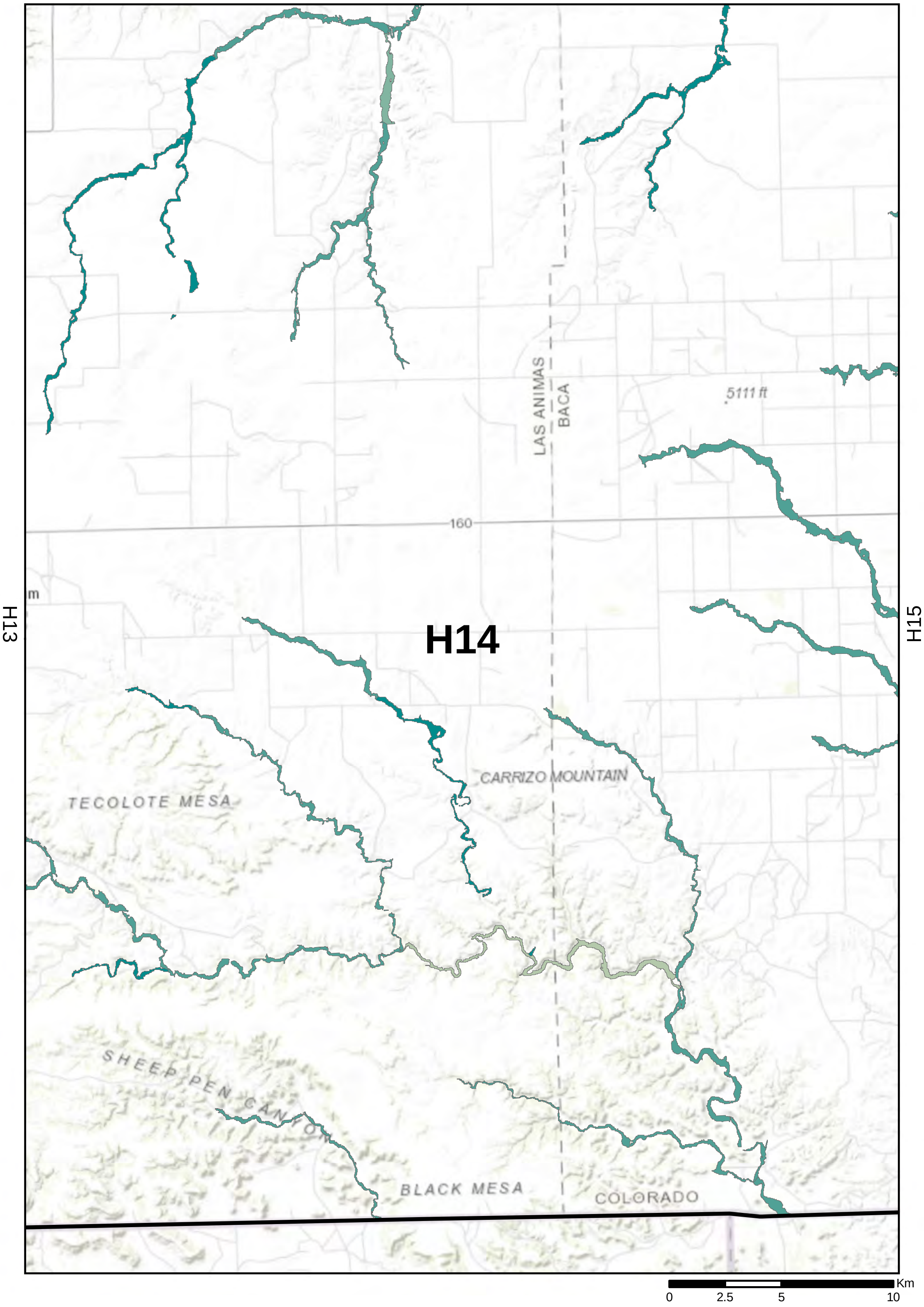
0 2.5 5 10 Km


G12
BIG ARROYO HILLS
Pinon Canyon Military Reservation
THE HOGBACK
THE HOGBACK
H11
H12
H13
PIÑON RIDGE
160
160
Branson
7221 ft
COLORADO
Km
0
2.5
5
10

G13

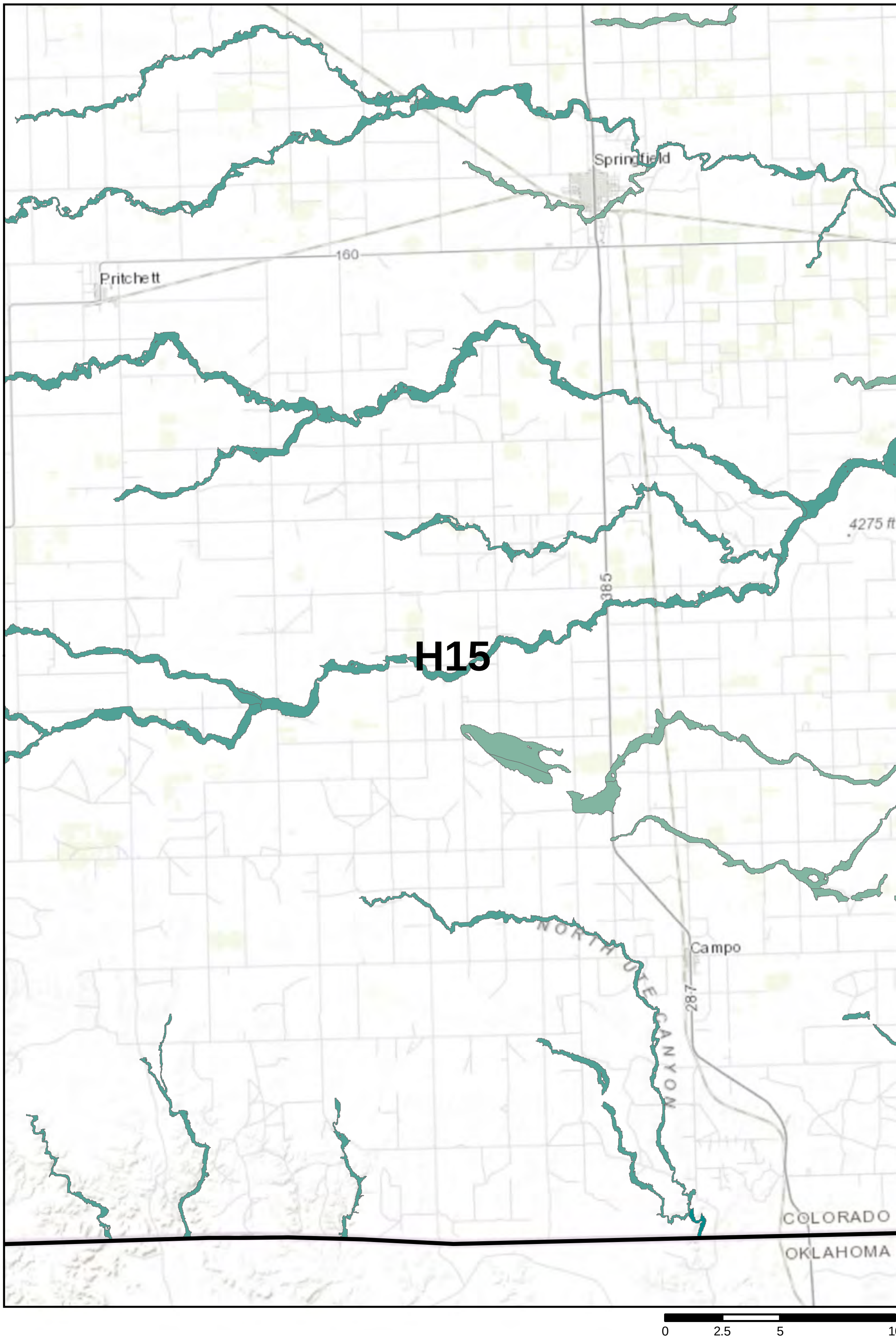

H12
H13
H14
State Highway 109
160
MESA DE MAYA
6560 ft
JESUS MESA
COLORADO
NEW MEXICO
0
2.5
5
10
Km

G14


H14
H13
H15
LAS ANIMAS
BACA
5111 ft
160
CARRIZO MOUNTAIN
TECOLOTE MESA
SHEEP PEN CANYON
BLACK MESA
COLORADO
Km
0
2.5
5
10

G15

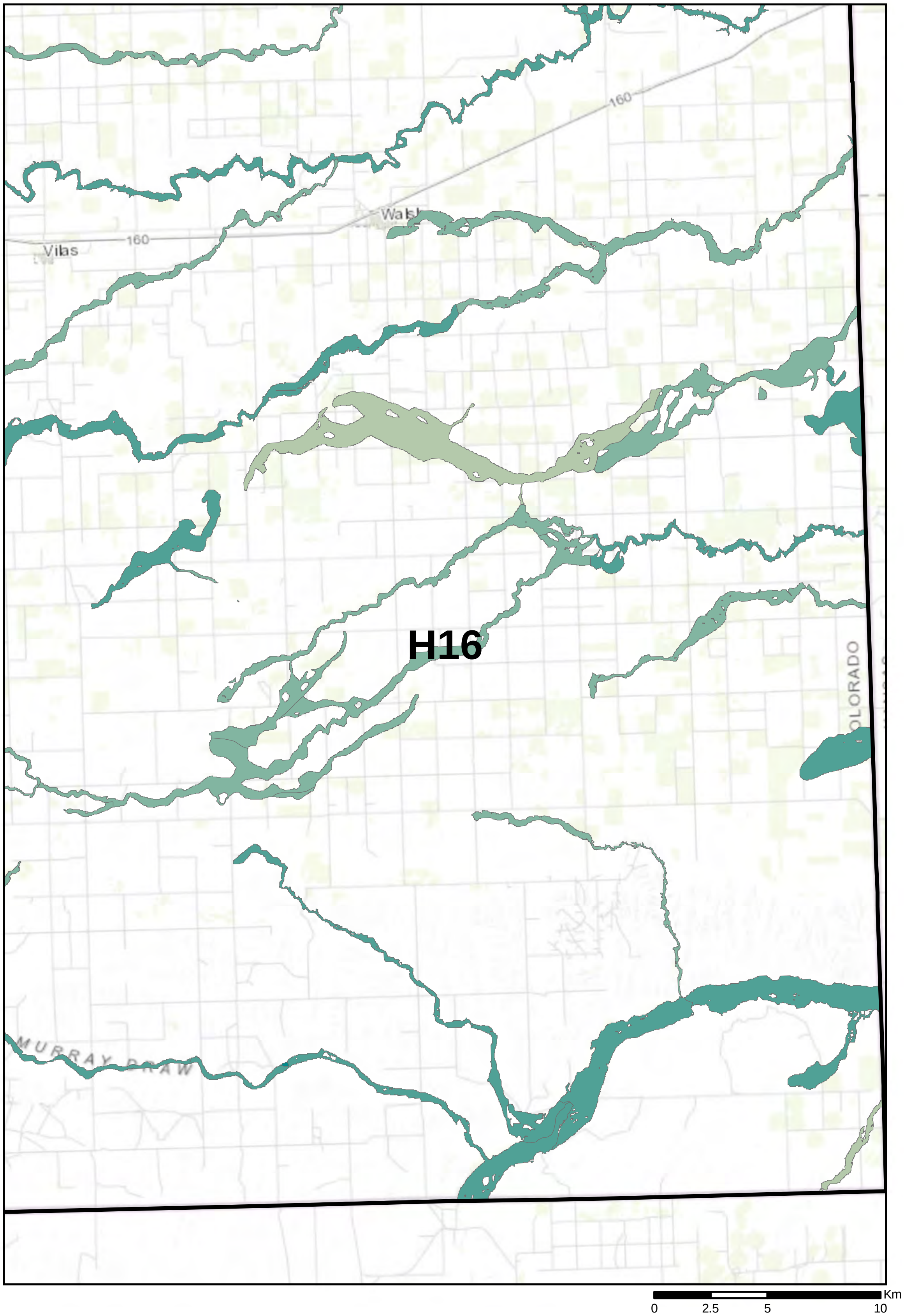
H14



Springfield
160
Pritchett
4275 ft
385
H15
Campo
287
NORTH UTE CANYON
COLORADO
OKLAHOMA

H16

G16



H15