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Exploring Farmers' Willingness to Accept Payment for Agricultural Conservation in Utah

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by

Asif Ahmed Khan

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of

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ABSTRACT

Exploring Farmers' Willingness to Accept Payment for Agricultural Conservation in Utah

by

Asif Ahmed Khan, Master of Science

Utah State University, 2024

Major Professor: Dr. Man Li
Department: Applied Economics

Utah faces water scarcity exacerbated by severe droughts, exemplified by the 2021–2022 period when the Great Salt Lake reached a historic low. With agriculture consuming 82% of the state's water, Utah enacted legislation allocating $200 million for agricultural optimization in 2023. This paper investigates irrigators' willingness-to-accept (WTA) payments for adopting water-conserving practices in agriculture. Over 80% of Utah's consumptive water is used in agriculture, necessitating a deeper understanding of farmers' economic threshold for water conservation. The study utilizes remote sensing, GIS, and econometric models with two main objectives: 1) constructing a spatial database of cropping patterns and net revenue in the Great Salt Lake Basin, and 2) developing a discrete choice model to assess irrigators' WTA for water-saving technologies. The integration of economic theory, econometrics, and GIS technology enhances the study's robustness. By providing an alternative to costly survey data through the use of remote sensing data, the research contributes to a spatially explicit analysis of farmers' choices, offering valuable insights for policymaking. Estimating

WTA payments, this study informs incentive-based policies crucial for sustaining Utah's agriculture and water resources, with broader implications for regions facing analogous water conservation challenges.

(48 Pages)

PUBLIC ABSTRACT

Exploring Farmers' Willingness to Accept Payment for Agricultural Conservation in Utah

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In view of Utah's drought situation and the need for conservation of water use, this thesis tries to calculate the compensation required for farmers to switch from cultivating alfalfa-which requires a lot of water, to less water-consuming crops like wheat, hay and even pasture. It proposes a new technique for this calculation using big data, including satellite images from National Aeronautics and Space Agency (NASA), agricultural statistics from National Agricultural Statistics Service (NASS), climate data from Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate group and land use data from the state of Utah. These data are integrated into a geographical database (geodatabase). The database is then used to create mathematical models that calculate the compensations. This is only one application of the database, which can be used for analysis to develop policies among other things. The process proposed here can give versatile support to policymakers and is much less time-consuming than commissioning and executing surveys or other manual modes of data collection.

DEDICATIONS

To the people of Utah and USU, who have been most welcoming, kind and supportive.

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Asif Ahmed Khan

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1. Introduction

Known for its arid and semi-arid climate, Utah has long experienced periodic droughts and water shortages. Importantly, the state faced its worst drought in 2021–2022, during which the Great Salt Lake (GSL) reached its lowest water level (4,190 feet) on record, about 20 feet below its peak elevation in 1987. In the long run, this could become a crisis because dust from the drying GSL poses a growing threat to Utah's economy, ecosystems, and public health. Airborne sediments from the dry-up lakebed carry heavy metals. These heavy metals accumulate over time in sediments from industrial, agricultural, and urban sources of pollution. Although the total amount of water in the main tributary watersheds of the GSL has not decreased significantly, the amount of water entering the GSL has shown a downward trend, due to increased water withdrawals (Wurtsbaugh et al., 2016; Null and Wurtsbaugh, 2020) Utah's steady population growth is one reason for the increase in water withdrawals. Over the 2011-2020 decade, the state's population has grown at an average annual rate of 7.4%, highest among U.S. states (U.S. Census Bureau, 2021). While the drought has been somewhat mitigated through record-breaking precipitation in winter 2022–2023 (Lang and Skiles, 2023), Utah must develop policies to tackle prolonged droughts through optimum water management.

By far agriculture (irrigation) is the most water intensive sector in Utah, accounting for about 70-85% of the state's consumptive water (Barlow, Chad et al., 2021). As such, it is the most critical sector for the application of water use management and optimization strategies. In 2023, the Utah Legislature passed SB 277, which appropriated $200 million for agricultural optimization and created a new committee named Agricultural Water Optimization Task Force (AWOTF) housed within the Utah Department of Agriculture and Food. The task force's annual report identifies finding alternative crops as one of its key research goals (AWOTF Annual Report, 2022).

The report stresses the imperative to maintain or enhance viable agriculture and is underscored by a particular emphasis on the water user. It also explores why water users have not adopted optimized water consumption practices and how to effectively approach this challenge. This study aims to contribute to the process of enabling users to conserve water by investigating farmers' WTA for water conservation in agriculture.

About 80% of the state's consumptive water is used for agriculture and there are comparative advantages of agricultural water conservation over other water conservation options- such as optimizing water pricing, limiting municipal and industrial water use growth, and cloud seeding- in terms of implementation cost and policy feasibility. Hence, it is critical to prioritize water conservation efforts in the agricultural sector of Utah to achieve the state's water conservation goals. Efficient water-use and conservation in agriculture are essential for preserving water resources and maintaining a sustainable farming industry. The literature highlights the importance of crop selection and management practices. Planting drought-tolerant crops, adopting crop rotation strategies, and implementing soil conservation measures can significantly reduce water demands while maintaining agricultural productivity. One of the key measures to quantify the economic threshold for farmers to adopt water conservation measures is their willingness-to-accept (WTA) payments for adoption of water conserving, i.e., less water intensive crops. Villamayor-Tomas et al. (2019) explore the possibility of implementing conservation frameworks and posit that coordinated programs are implementable through mitigating the transaction costs and monetary/social incentives. Ding and Peterson (2012) showed that providing compensation to farmers for switching to less water intensive crops can reduce water consumption, especially when there is a shortage of water. Haile et al. (2019) discuss how farmers' WTA payments can be leveraged to promote climate-smart agroforestry while Nyongesa et al. (2016) explore the same principle for ecosystem services in Kenya.

The objective of this paper is to explore irrigators' WTA payments spatially explicitly for irrigation water conservation by utilizing publicly assessable remote sensing (RS) products and integrating geographic information system (GIS) and econometric models. For this purpose, this paper first constructs a 30-meter resolution spatial database of cropping pattern, irrigation systems, crop-specific net revenue from cultivation in the Great Salt Lake Basin for the period 2017–2022. Then, it develops an econometric discrete choice model based on the conceptual framework of random utility models and estimates how private landowners choose crop types in response to net revenues from crop cultivation using the 30-meter geospatial database. Finally, it assesses the spatially explicit landowners' WTA conservation payments in exchange for adopting less water-intensive or drought-tolerant crops.

This study contributes to the literature by integrating economic theory, econometric modeling, and GIS technology to address Utah's pressing water conservation issues. In contrast to many earlier studies- e.g., Nyongesa et al. (2016) and Haile et al. (2019)- that rely on costly and laborious survey data to estimate agents' willingness to pay, this study uses publicly available high-resolution RS products. However, the indirect method used in this study may be estimating a lower bound of WTA payments. Nevertheless, with flexibility and transparency, the model can be applied to any country or region interested in exploring the economic viability of natural resource and environmental conservation, including but not limited to water conservation in agriculture. More important, this study develops a cutting-edge method to assess crop yields and revenue at each site, which is critical to accurately estimating irrigators' WTA conservation payments. Regulators will need to gather information necessary to decide on the specific "orders" or design payment contracts. But in practice, collecting complete information remains challenging because measuring site-specific benefits and costs of conservation is laborious, expensive, and difficult to scale. Analysts and policymakers often estimate the expected water conservation potential of an irrigation modernization project by simply "scaling-up" improvements in this ratio, for example, by multiplying the incremental change in the efficiency ratio by the acreage of the project (Lankford, 2012). Although earlier studies have used economic theory and simulation methods to explore the potential of economic incentives to encourage water conservation in agriculture (Huffaker and Whittlesey, 2003; Huffaker, 2008) and empirically analyzed the factors influencing irrigation technological selection (Caswell and Zilberman, 1985, 1986; Green et al., 1996; Carey and Zilberman, 2002; Quintana-Ashwell et al., 2020), there lacks a spatially explicit analysis to thoroughly explore where it pays to conserve irrigation water. This study can fill this research gap and inform agricultural water conservation policies of possible tradeoffs and opportunities.

The remainder of this paper is organized as follows: Section 2 discusses the background of the study area. Section 3 describes materials and methods. Section 4 presents and discusses the results. Section 5 concludes.

2. Background of Study Area

In the western United States, irrigated agriculture relies heavily on snowmelt-driven instream flows from high-altitude areas. Low-snow years reduce water supply for downstream irrigation, while earlier-than-normal spring snowmelt can cause instream flow to peak a week or weeks earlier than usual. Both of these conditions lead to abnormally low river flows in spring and early summer (Cayan et al., 2001; Stewart et al., 2005); Utah has experienced decreased precipitation, warmer temperatures, and a shift in precipitation from snow to rain since 1950 (Gillies et al., 2022). During the period 1950–2021, total precipitation has decreased for an average of nine months a year, with the driest critical months from March to August, which coincides with the crop irrigation season. Temperatures rose in all months during the same period except October. Most of Utah's water supply comes in the form of winter and early spring snowpack. Historically, January through March are the most productive snow accumulation months. As shown in Fig. 1 (US National Integrated Drought Monitor System [NIDIS]), total precipitation over this period has declined slightly. In addition, the typical snow accumulation months, November to May, experienced more frequent rainfall as temperatures warmed. The impact of higher winter rainfall is mostly negative because there is less snowpack to hold water. These winter trends have accelerated in Utah's lower and mid-elevation regions, further stressing the state's water supply.

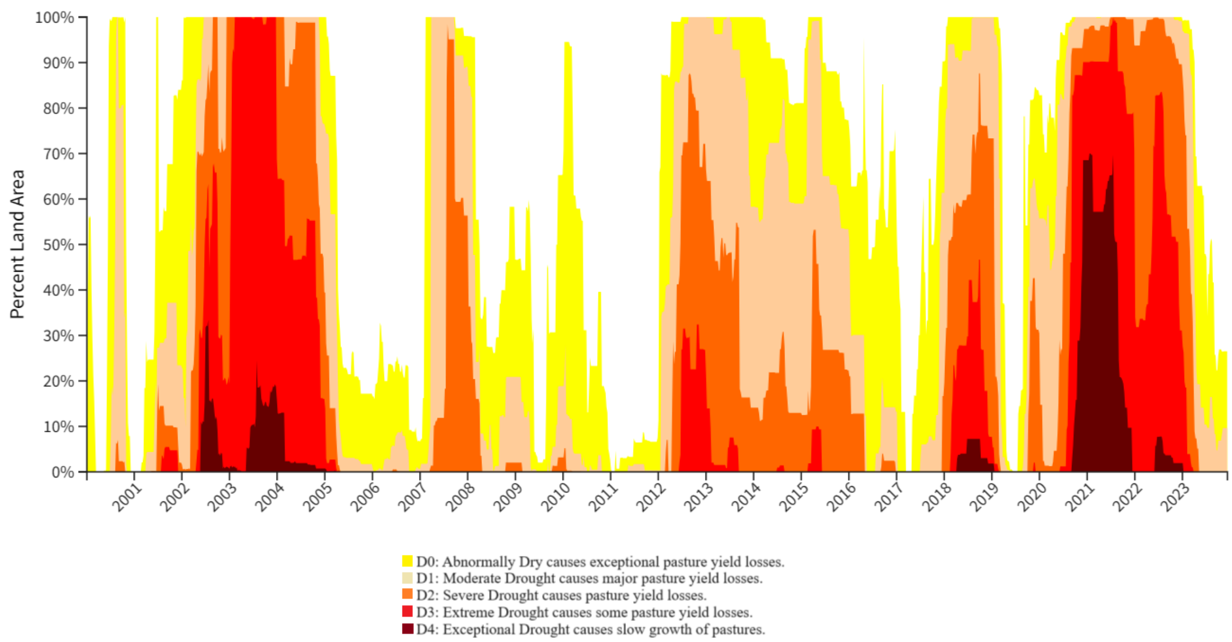

Fig. 1 Drought timeline of Utah

Three main tributary watersheds of the GSL in Utah—the Bear River Basin, the Weber River Basin, and the Jordan River Basin (including the Utah Lake sub-basin)—are selected for analysis in this proposed project (Fig. 2). These watersheds are Utah's major agricultural production regions and cover about 12 counties. Consumptive water uses in these watersheds contributed to approximately 39% of the decline in inflows, of which 63% was used for irrigated agriculture (Wurtsbaugh et al., 2017). The main irrigation methods include flood, sprinkler, and drip (Utah Open Water Data, 2023). Alfalfa and hay account for a large proportion of cultivation, supplemented with field crops, grain and seeds, orchard, and small fruits (Cropscape- Cropland Data Layer, 2023). Some pastureland is also irrigated (Utah Open Water Data, 2023). Understanding the potential for agricultural water conservation in these regions not only helps sustain rural communities but has important implications for GSL conservation.

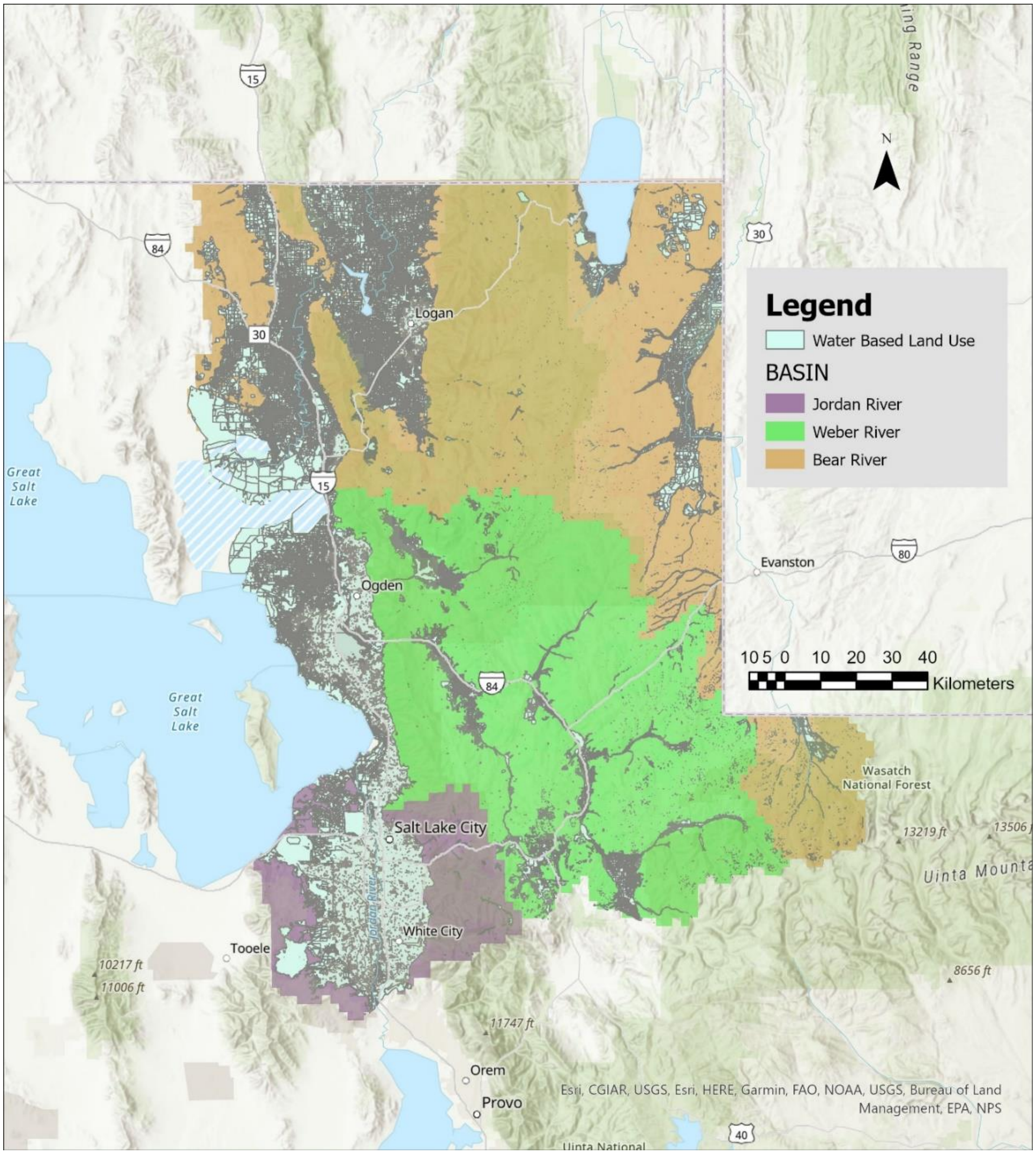

Fig. 2 Study area basin map

3. Materials and Methods

This study employs a comprehensive research design to analyze diverse agricultural and environmental datasets, integrating spatial-temporal information from various sources. Subsection 3.1 describes data sources and processing process. Subsection 3.2 describes the data sampling strategies. Subsection 3.3. presents the empirical model for estimating the crop choice model and calculating the WTA payments.

3.1. Data

This study combines a series of spatial-temporal data files for the period 2017–2022 for analysis. The data files include the Cropland Data Layer (CDL) by National Agricultural Statistics Service (NASS), Moderate Resolution Imaging Spectroradiometer (MODIS)-Enhanced Vegetation Index (EVI) from National Aeronautics and Space Agency (NASA), Water-Related Land Uses (WRLU) from the Utah Division of Water Resources, county boundary polygon shapefiles, agricultural statistics (land rent, crop prices, crop yields) from NASS's QuickStats 2.0 database portal, and land ownership data stewarded by the School and Institutional Trusts Land Administration (SITLA) & US Bureau of Land Management (BLM) & Partners hosted in the Utah Geospatial Resources Center (UGRC) website. Climate data from Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate group of Oregon State University is also used. Table 1 lists the data used in the analysis.

Table 1. Description of data and sources

Product	**Source**	**Note**
Cropland Data Layers	NASS	Annual, 30m raster, 2017–2022
MODIS-Enhanced Vegetation Index	NASA	16-day composite, 250m raster, 2017–2022
Water-Related Land Use Inventories	Utah Division of Water Resources	Annual, shapefile, methodology changed since 2017
Agricultural statistics	NASS	Annual, county or state, 2017–2022
Land ownership	SITLA & BLM & Partners	Cross-sectional, 2021 Data used for all years
Watershed boundary	Utah Division of Water Resources	Cross-sectional
County boundary	Utah Mapping Portal	Cross-sectional
Temperature and Precipitation	PRISM Climate Group, Oregon State Univ.	Monthly, 4km raster, 2017-2022
Elevation	Utah Mapping Portal	Cross-sectional
Basin	Utah Mapping Portal	Cross-sectional

CDL Land Use. The CDL, accessible through CropScape, furnishes a detailed, geo-referenced, crop-specific land cover map for the continental United States. The data, created annually using moderate resolution satellite imagery, includes essential information such as crop types and land cover details at a resolution of 30m. CDL has identified more than 80 crops in Utah. To eliminate minor crops and improve model performance, CDL land uses are grouped into eight categories in descending order from water-intensive to drought-tolerant: fruits (1%), alfalfa (30%), non-wheat grain crops (6%), non-alfalfa hay (9%), pasture (26%), wheat (13%), other minor crops (3%), and fallow (11%).

EVI Data. MODIS, an instrument aboard Terra and Aqua satellites, offers a 16-day, 250m resolution raster of EVI. Calculated based on specific coefficients, EVI is a measure of vegetation canopy greenness and has been broadly applied in the literature as an effective predictor of crop productivity. The annual maximum EVI is extracted from each year's 16-day frequency EVI images and used to calculate spatially explicit crop net returns.

EVI-based Net Returns Data. To capture the response of each farmer's cultivating decision to changes in agricultural profits, it is necessary to know crop revenue and then net returns at each site. In the absence of site-specific crop yields, this study combines the county-level crop revenue[1], cropland rent, pastureland rent, with CDL and EVI to calculate crop revenue and net returns for each 30-meter pixel each year. Here, land rents

[1] County-level crop revenue is obtained by multiplying county-level crop yield by state-level crop price.

serve as a proxy for net returns from growing crops (excluding the costs of producing the crop other than the land). First, rent to revenue ratio is calculated for every county; then this ratio is multiplied with the pixel-specific revenue and scaled by multiplying with the ratio of pixel-specific EVI and average EVI that year for the specific crop type in that pixel to avail the net returns measure. This is justified as in long-run equilibrium, farmers make no difference between farming their own land and leasing it to other farmers.

The raw datasets are processed into a comprehensive shapefile using ArcGIS's arcpy library. CDL shapefiles for the years 2017 to 2022 serve as the base shapefile, with additional variables such as EVI, county, basin, and irrigation added through a systematic processing workflow. The shapefiles are subsequently converted into tabular comma-separated values (.csv) format, facilitating data modeling in the programming language R. It is important to note that landownership is categorized into federal, state, tribal, and private ownership. This study focuses only on private cropland and pastureland.

3.2. Sampling Strategy

There are two potential econometric issues in the analysis of spatial-temporal land-use data. The first problem is spatial autocorrelation, which arises from the presence of unobserved factors correlated over space. Estimation inefficiencies can result if some unobserved factors influence the land-use choices of adjacent land units. To address the inherent spatial autocorrelation in the dataset, this study adopts a spatial sampling scheme by taking a 1-out-of-9 sample by choosing only the centroid cell of a 90 × 90 m grid. This sampling scheme was developed by Besag (1974) and later applied in many land-use studies. Compared to the more efficient strategy of specifying aspheric error variance-covariance matrices (and therefore more computationally intensive), the spatial sampling strategy has the advantage of systematically thinning out the dataset and avoiding intensive computation (Li et al. 2015). This strategy is particularly suitable for large datasets, facilitating the creation of a refined dataset characterized by reduced point density while retaining the essential properties of the comprehensive original dataset.

Another problem with the data is the nature of repeated pixels in a panel data set. To exploit the panel structure while avoiding econometric problems such as autoregression, this study implements stratified sampling, where each pixel is treated as a stratum and only one observation (i.e. one year) is randomly selected in each stratum. This method aimed to maintain a uniform distribution by systematically extracting samples from all delineated areas covered in the map. By adhering to a stratified sampling approach, the resultant subset of points retained its representative nature, offering a balanced reflection of the diverse characteristics present across the entire spatial extent. This meticulous sampling technique adds a layer of precision to the data thinning process, reinforcing the integrity of the subsequent analyses conducted on the thinned dataset.

These two sampling strategies reduce the sample size to 281,072 observations, which are further randomly divided into two equal-sized training and validation samples. Training data of 140,536 observations are used for model estimation.

3.3. Empirical Model

Discrete choice models are well suited for analyzing farmers' crop selection decisions. These models are used ubiquitously in estimating the probability of a specific land use choice to be made. The underlying principle of this modeling framework arises from the revealed preference theory which supposes that the chosen use of a particular area of land is the result of a profit-maximization process on the individual's part. The empirically observed discrete choices can be modeled/explained using factors assumed to affect the returns availed from the land-use. Given the characteristics of each location, the probability for a particular land use being chosen can be calculated for each relevant location using a discrete choice model.

Consider a farmer who makes crop choices in period t to maximize the expected net benefit from the land parcel, where land parcels are indexed by n; $n = 1, \dots, N$. The land could be allocated to J mutually exclusive alternative uses, indexed by j; $j = 1, \dots, J$. The expected net benefit generated from choice j on land parcel n is U_{njt}. Alternative j for land parcel n at time t is chosen if and only if $U_{njt} > U_{nkt}\ \forall j \neq k$. A standard practice in a discrete choice modeling setup is to decompose U_{njt} into a non-stochastic component, V_{njt}, and a stochastic error term, ε_{njt}, i.e., $U_{njt} = V_{njt} + \varepsilon_{njt}\ \forall j, t$. The probability that alternative j is chosen on land n in period t is-

$$P_{njt} = \Pr\left(U_{njt} > U_{nkt}\ \forall j \neq k\right), \quad (1)$$

Assuming that ε_{nj} follows Gumbel (type-I generalized extreme value) distribution, the choice probability takes logistic functional form (McFadden, 1977)-

$$P_{njt} = \frac{\exp(V_{njt})}{\sum_{k=1}^{J} \exp(V_{nkt})} \quad \forall\, n, j, t, \tag{2}$$

where $\exp(\cdot)$ is the exponential function and V_{njt} (which is linear in parameters, thereby simplifying analysis) is specified as-

$$V_{njt} = \boldsymbol{D}_{nt-1}\boldsymbol{\alpha}_j + R_{njt}\beta_j + \boldsymbol{Z}_n\boldsymbol{\gamma}_j + \tau_t,\ \ t = 2018, \dots, 2022. \tag{3}$$

The term $\boldsymbol{D}_{nt-1}$ represents a vector of lagged crop choices in period $t-1$—an inertia variable to capture unobserved land-use conversion costs as well as the location-specific characteristics such as agroecological and agroclimatic conditions. This empirical strategy has been applied in the econometric land-use modeling literature (Li et al., 2013; DePinto et al., 2016; Li et al., 2021, 2022). The term R_{njt} is the spatially explicit per-acre net returns to land created in Section 3.1 (EVI Based Net Returns Data, P. 12). The term $\boldsymbol{Z}_n$ is a set of categorical variables indicating county and watershed dummies. The term τ_t indicates time period dummy, which captures the effects of a particular year on the land-use choice. The logistic model in (2) is estimated in pooled regression using the training data generated in Section 3.2. Notably, stratified sampling ensures that only one period of each pixel is selected, which eliminates potential autocorrelation; again, endogeneity is mitigated through inclusion of lagged choice as a covariate.

3.4. Willingness-to-accept Water Conservation Payments

Let WTA_{njk} be a farmer's per-acre WTA water conservation payments in exchange for switching from a water-intensive crop j to a drought-tolerant crop k on land n. The following must hold for minimum WTA:

$$\hat{V}_{njt} = \hat{V}_{nkt} + WTA_{njk}\hat{\beta}_k. \tag{4}$$

where $\hat{V}_{njt}$ and $\hat{V}_{nkt}$ are predicted V_{njt} and V_{nkt}, respectively; $\hat{\beta}_k$ is the point estimate for β_k. Notably, this is different from equation (1), where j stands for chosen crop and k stands for other crops, respectively. In addition, $\hat{\beta}_k$ converts WTA_{njk}, which is in USD per acre, to utility measure similar in unit to V. Rearranging (4) yields-

$$WTA_{njk} = \left(\hat{V}_{njt} - \hat{V}_{nkt}\right)/\hat{\beta}_k. \tag{5}$$

Thus, $\left(\hat{V}_{njt} - \hat{V}_{nkt}\right)/\hat{\beta}_k$ is the lower bound of farmers' per-acre WTA for changing from crop j to crop k at location n.

4. Results

The chosen modeling approach, multinomial logit, is suited for the dataset's categorical nature. The model calculates coefficients to predict agricultural choices for the subsequent year based on various independent variables. These include crop choice $\boldsymbol{D}$, basin, county (both covered by $\boldsymbol{Z}$), year τ and net returns R.

The table below illustrates the coefficients resulting from the regression on equation (3).

4.1. Estimation results

Table 2. Estimation results of the multinomial logit model

Dependent variable	Pasture	Alfalfa	Hay	Fruit	OtherGrain	Wheat	OtherCrop
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Net returns	552.623***	552.606***	552.531***	552.722***	552.594***	548.489***	552.623***
(Std. Error)	(0.354)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Lagged Choice	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Basin fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared				0.85			
Marginal effect	-0	1.85	-1.25	0	0.021	-0.82	0.018

Notes: *p<0.1; **p<0.05; ***p<0.01

Fallow is the reference choice. The marginal effect is amplified by 100.

Even without the inclusion of weather variables, the results are robust as indicated by the high pseudo R-squared value. This parameter also highlights the importance of lagged choices and fixed effects. Marginal effects of profit on crop choice (probability) provide insights into the impact of revenue on crop choice, i.e., the sensitivity of choice probability, hence utility, to changes in crop selection.

As such, using this data, equation (5) yielded the site-specific minimum WTA payments for farmers to switch from alfalfa to hay, wheat and pasture. Table 3 presents the summary statistics of these WTA payments. It shows that encouraging farmers to switch to hay is the least costly option. Further, as hay is a substitute for alfalfa, its price should rise with the reduction in alfalfa production, adding incentive for the farmers.

Table 3. Summary statistics of farmers' per-acre minimum WTA to switch from alfalfa

Crop	Mean (USD/acre)	Median (USD/acre)	Standard Error
Hay	2.9	2.5	0.007
Pasture	58.8	49.4	0.136
Wheat	5.3	4.5	0.012

Mapping the WTA payments at the corresponding locations provides insights into the spatial characteristics of the target parameter.

4.2. Farmers' WTA Payments for Agricultural Water Conservation

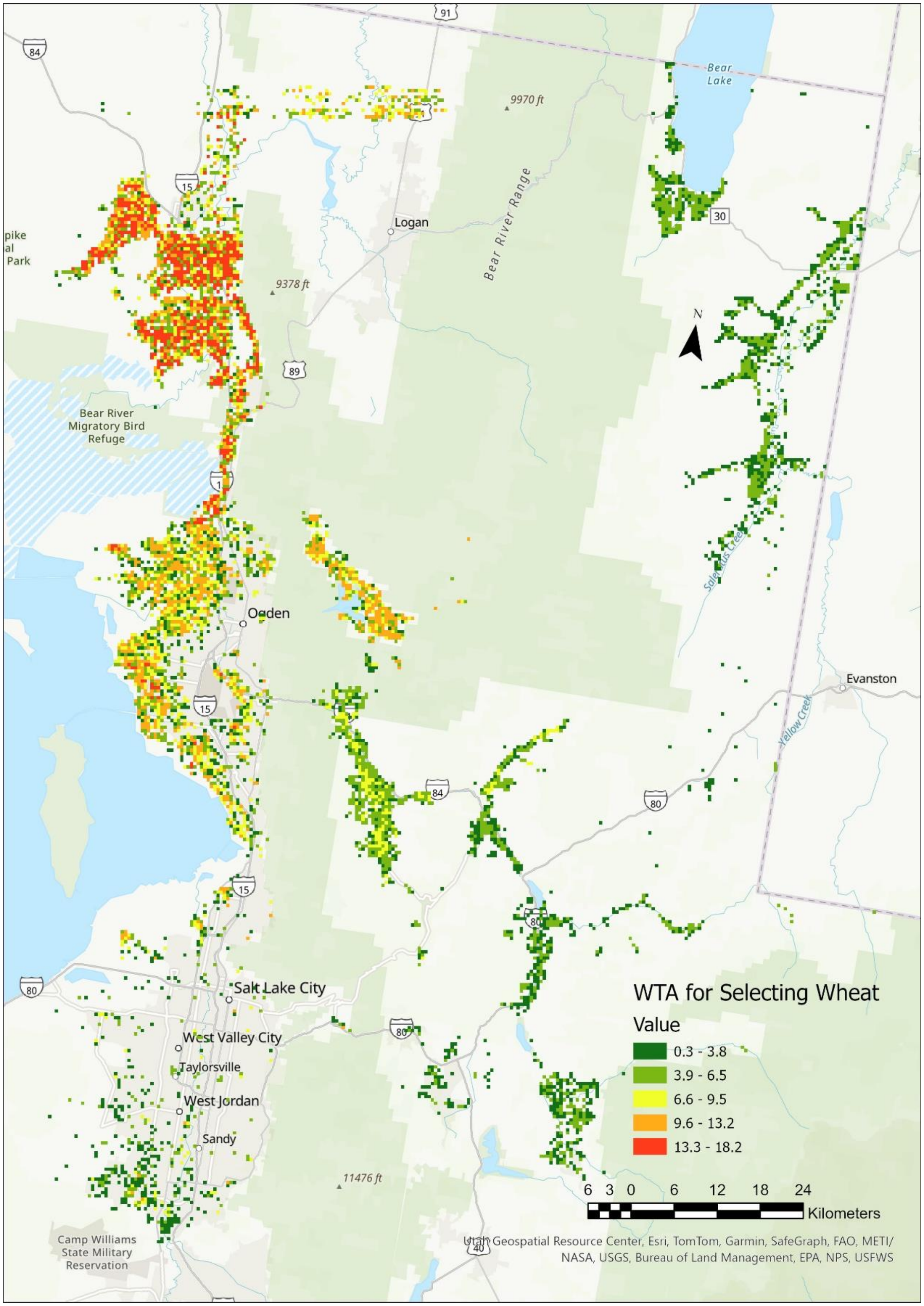

Fig. 3 WTA amount for replacing alfalfa with wheat.

From the figure it is visible that the cost to switching from alfalfa to wheat is lower in the north-western counties like Rich, Logan, Davis and Summit is lower than that of north-eastern Box Elder. The dollar amount varies from $0.30 to $18.20 per acre. The amounts are lower is Rich than all other counties. Box Elder shows much higher values because the profit for alfalfa is higher compared to other counties under consideration. A progression of increasing WTA is observed from east to west as profits from alfalfa increase in that direction. The following histogram gives a general idea about the distribution of WTAs.

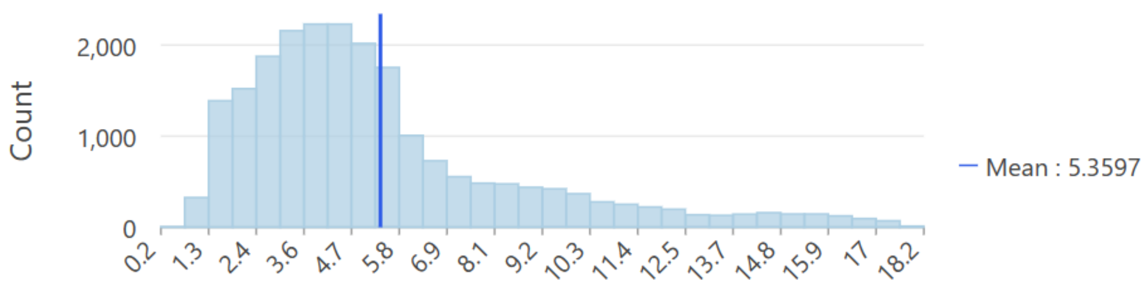

Fig. 4 Distribution of WTA amount for replacing alfalfa with wheat.

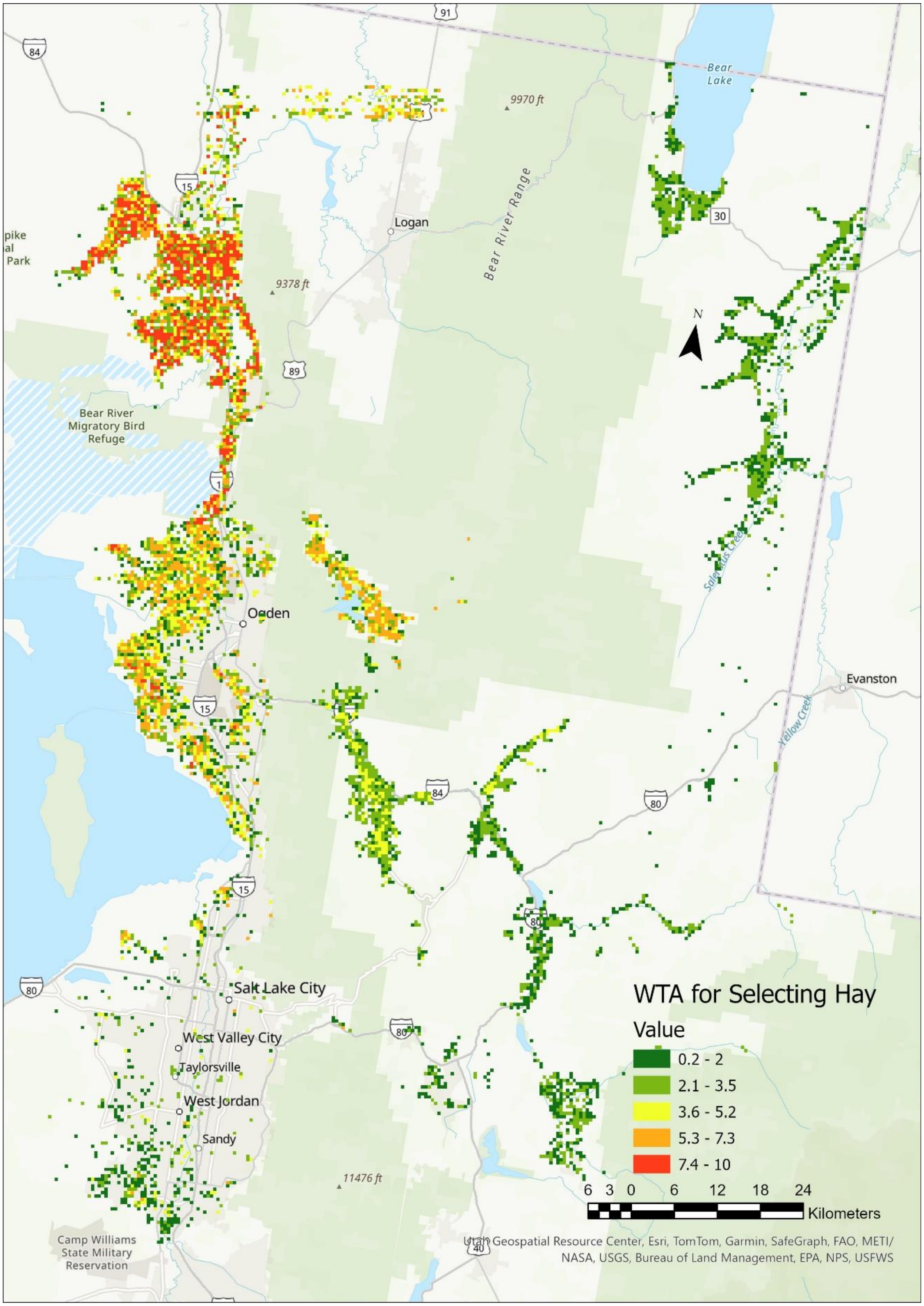

Fig. 5 WTA amount for replacing alfalfa with hay.

The map in figure 4 delineates the WTA of switching from alfalfa to hay. The costs are similar to switching from alfalfa to wheat. In addition, it is found the cost of switching is significantly less in Rich county than in Box elder. Since the profit from hay is in general greater than the profit from wheat, WTA tends to be slightly lower per acre for hay than for wheat. Again, Box Elder shows much higher values because the profit for alfalfa is higher compared to other counties under consideration. A progression of increasing WTA is observed from east to west as profits from alfalfa increase in that direction. The following histogram gives a general idea about the distribution of WTAs.

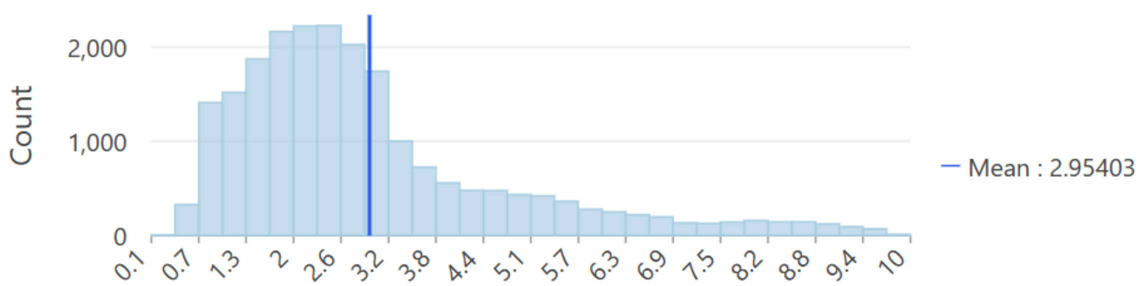

Fig. 6 Distribution of WTA amount for replacing alfalfa with hay.

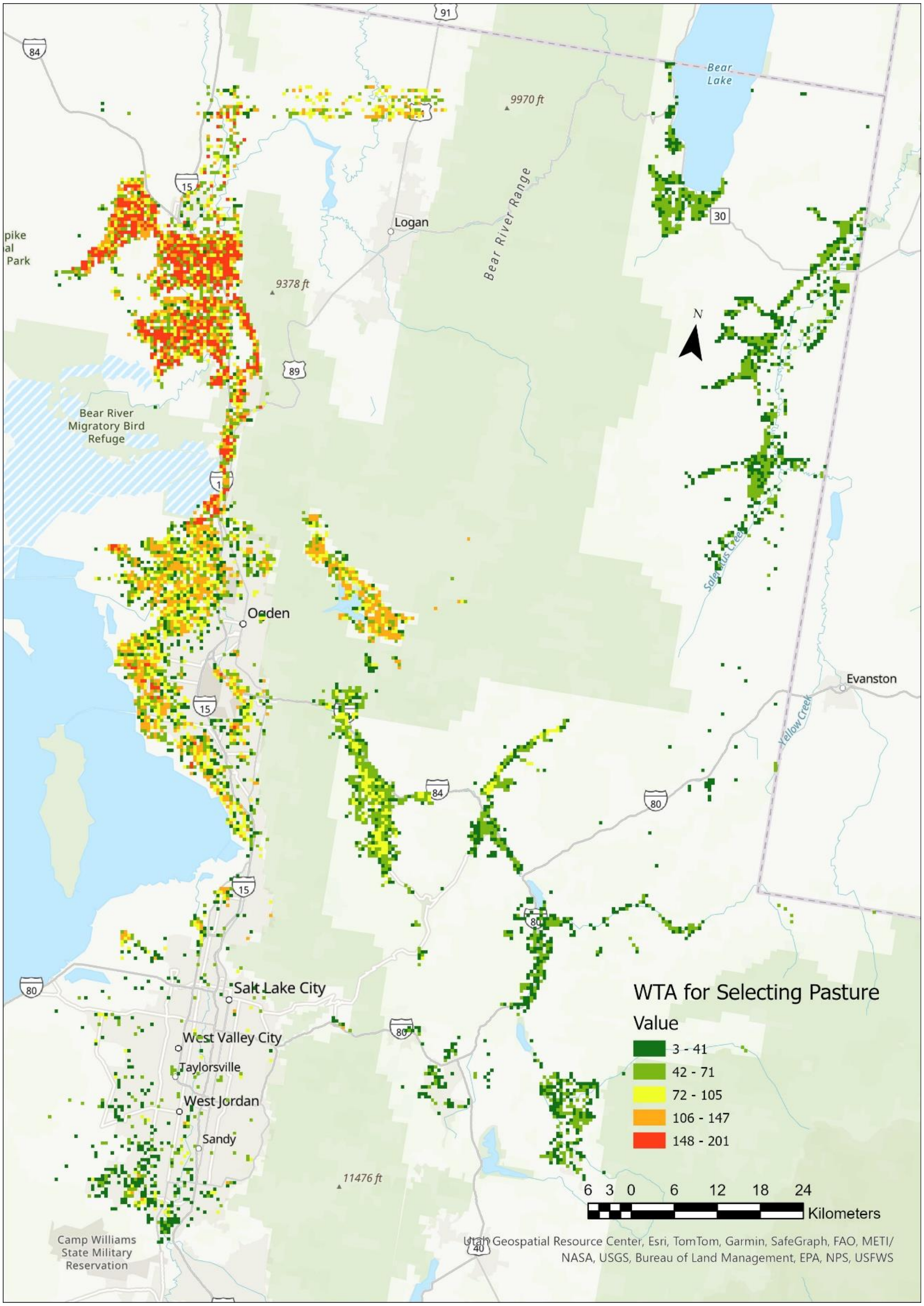

Fig. 7 WTA amount for replacing alfalfa with pasture.

Figure 5 shows the WTA of switching from alfalfa to pastureland. As expected, the cost of switching is high given the low revenue generation of pasturelands. Again, the cost of switching is lower in the county of Rich than it is in Box Elder, with a progressive increase observed moving east to west. The following histogram gives a general idea about the distribution of WTAs.

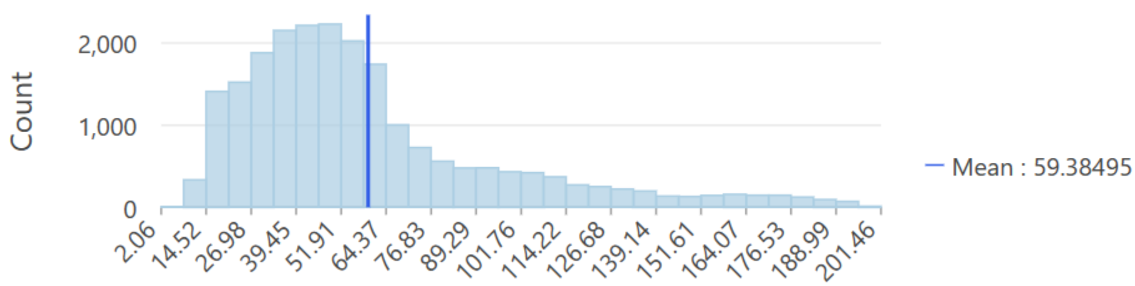

Fig. 8 Distribution of WTA amount for replacing alfalfa with pasture.

4.3. Farmers' Revenue Loss Due to Agricultural Water Conservation

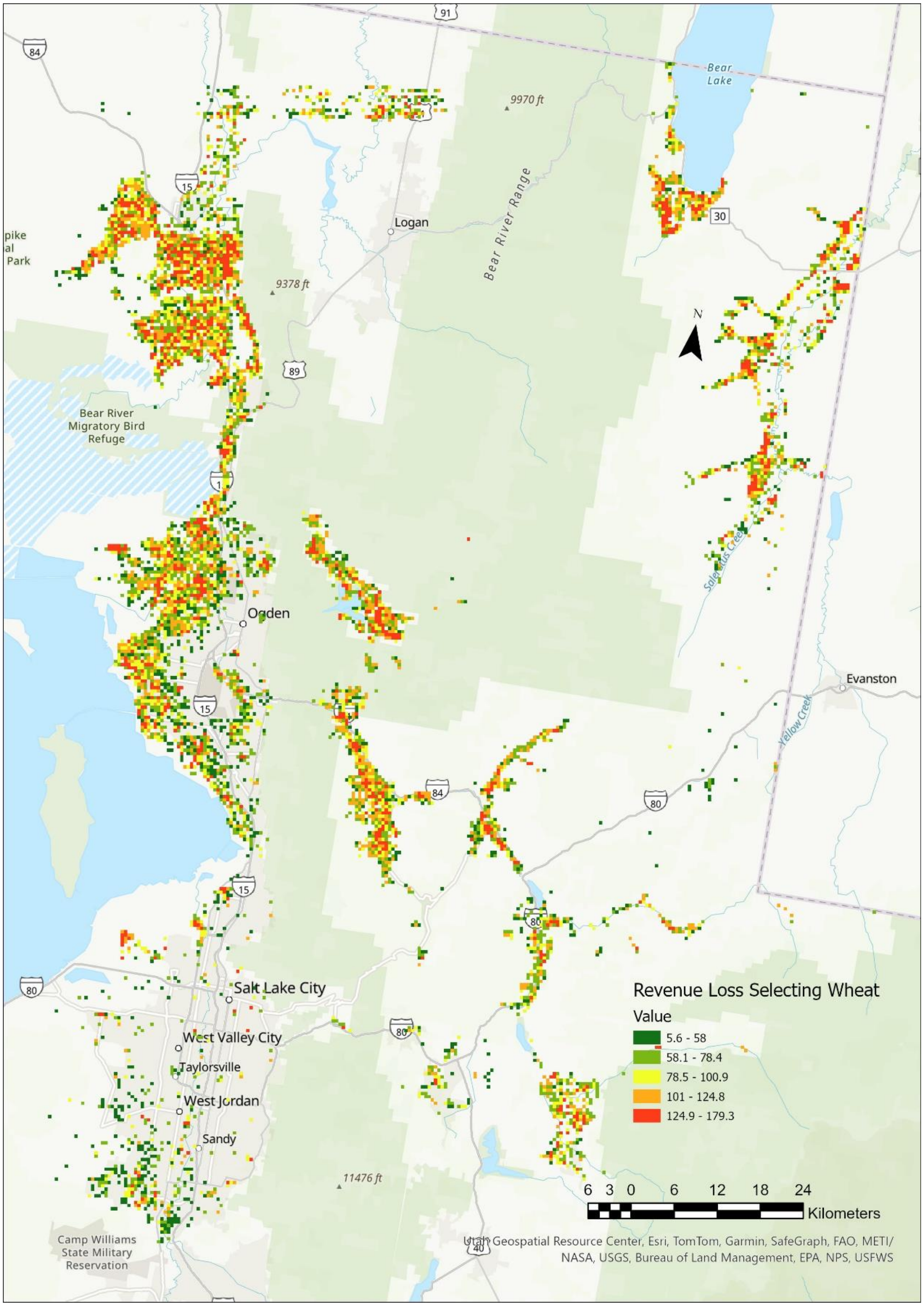

Fig. 9 Revenue loss for replacing alfalfa with wheat.

To understand the reason behind differing switching costs from alfalfa between counties and crops, revenue loss maps were generated for the points with available irrigation data. Figure 6 shows the revenue loss of switching from alfalfa to wheat per acre. As clearly visible from the map, the revenue loss per acre is much higher in Box Elder and much lower in Cache and Rich counties. As a result, farmers' WTA is much higher in Box Elder than in Rich County. Interestingly, revenue loss in Cache is in some cases lower than Rich. However, due to the higher overall revenue in Cache from alfalfa, the amount needed to reimburse farmers for switching to wheat from alfalfa is higher than the amount required in Rich. The following histogram gives a general idea about the distribution of revenue loss.

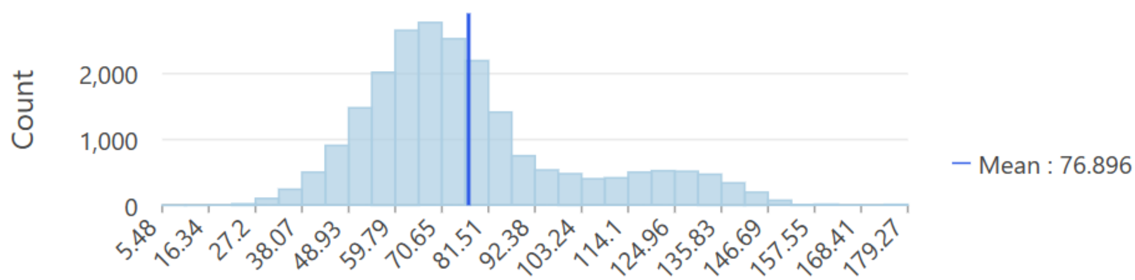

Fig. 10 Distribution of revenue loss for replacing alfalfa with wheat.

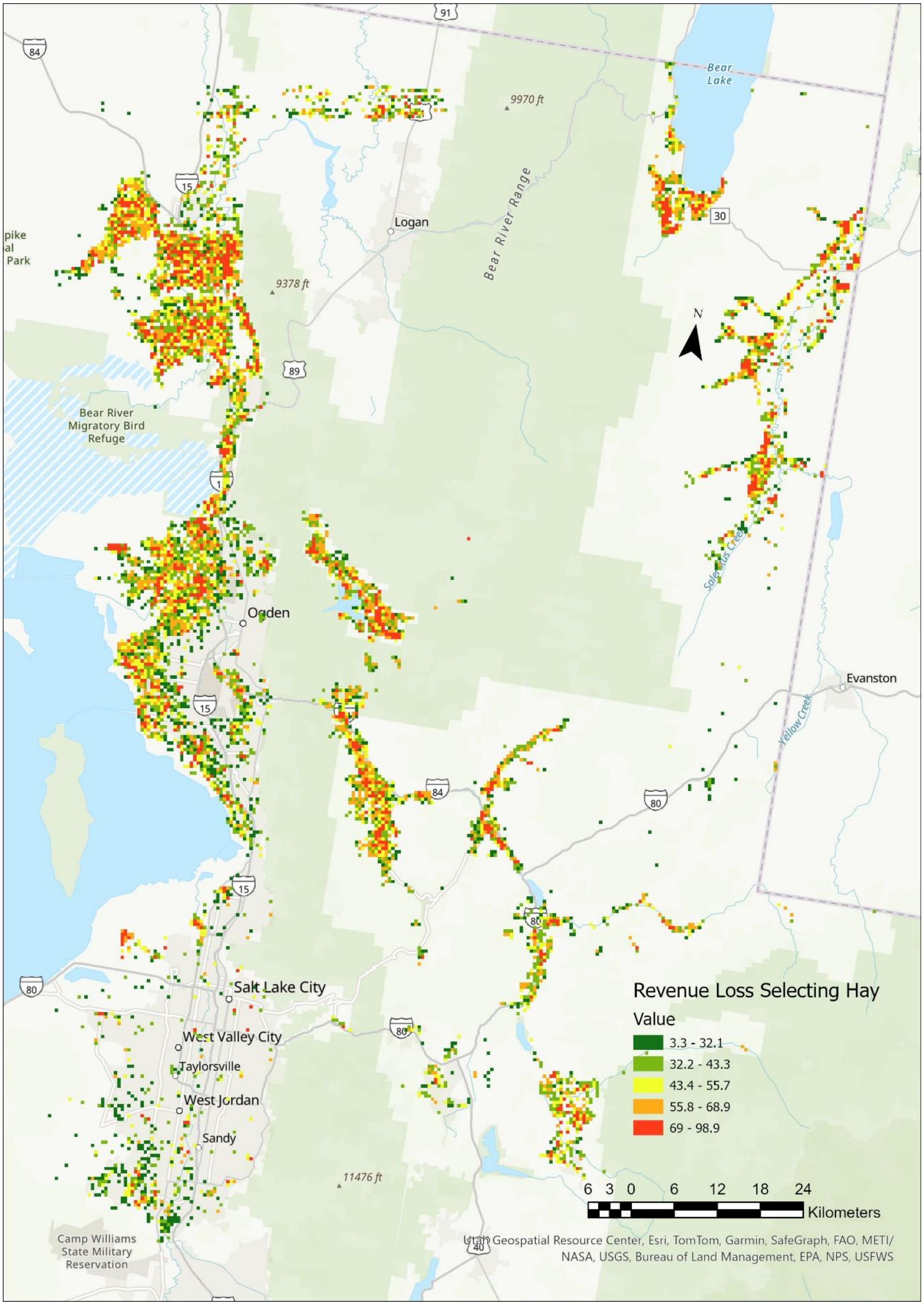

Fig. 11 Revenue loss for replacing alfalfa with hay.

Figure 7 depicts the revenue loss for switching from alfalfa to hay in the study area. Again, the loss in Rich county is lower than that in Box Elder. However, it is once more observed that the loss from switching is generally lower in Cache than in Rich. And yet, the higher production cost values in Cache account for the higher cost of switching form alfalfa as compared to Rich. The following histogram gives a general idea about the distribution of revenue loss.

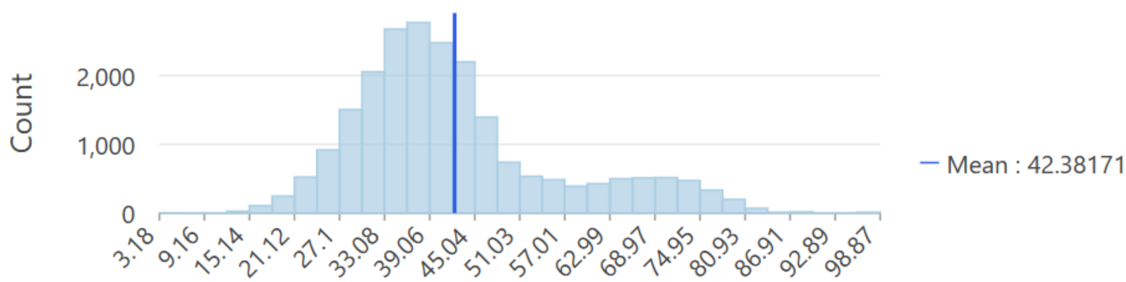

Fig. 12 Distribution of revenue loss for replacing alfalfa with hay.

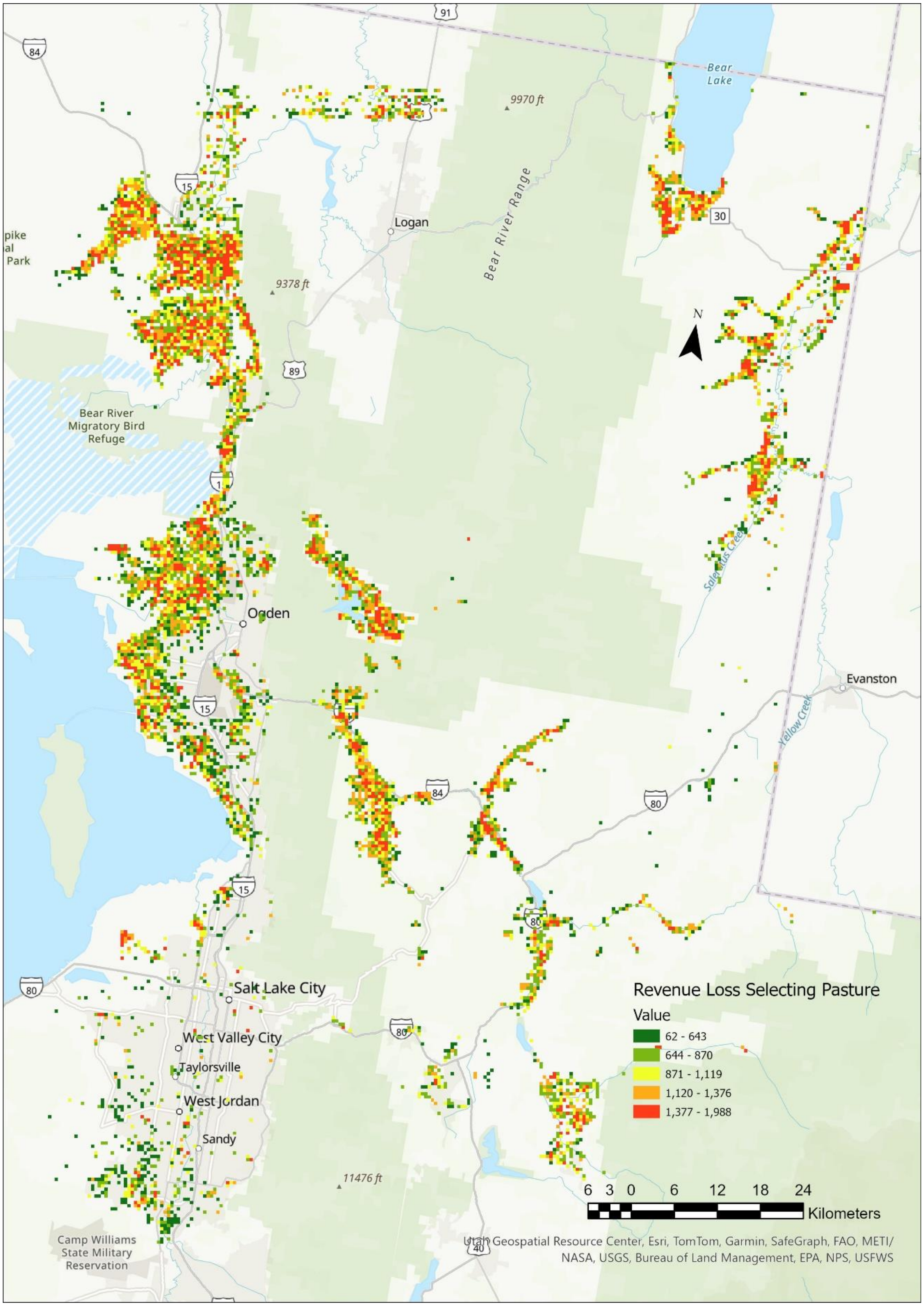

Fig. 13 Revenue loss for replacing alfalfa with pasture.

Figure 8 examines the revenue loss for switching from alfalfa to pastureland in the study area. The results are similar to the previous section area-wise, i.e., Cache county has the lowest loss and Box elder the highest. However, the loss amounts are much greater, accounting for the much lower revenues of pastureland compared to alfalfa. From the maps it is clearly visible that there is a spatial variance in WTA. The western part of the Wasatch front has relatively lower WTA amount than the central and eastern parts. Thus, it may be easier to introduce policy pilots in the regions with a lower WTA.

Further, it appears that hay as a natural substitute for alfalfa would appreciate in price should the production of alfalfa be reduced. As such, hay could be a prudent choice for farmers as replacement of alfalfa. The following histogram gives a general idea about the distribution of revenue loss.

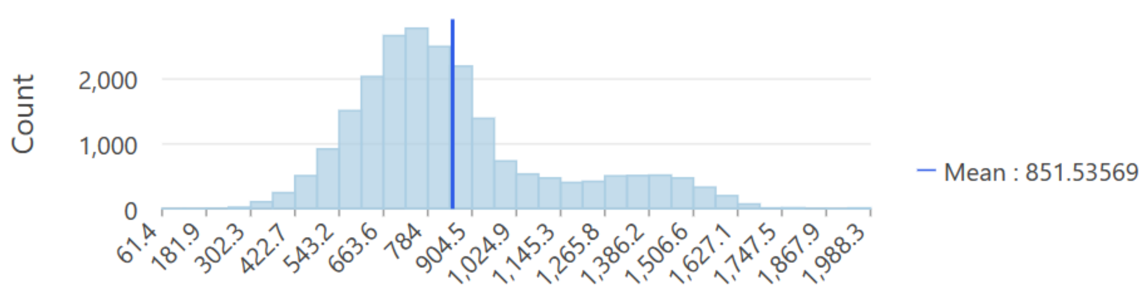

Fig. 14 Distribution of revenue loss for replacing alfalfa with pasture.

5. Conclusion

In light of escalating water scarcity exacerbated by severe droughts, highlighted by the historic low levels of the Great Salt Lake in 2021–2022, Utah has proactively responded with legislation allocating $200 million for agricultural optimization in 2023 (Utah State Legislature Bill S.B. 277). This substantial commitment underscores the state's recognition of the urgent need to address water consumption in agriculture, which currently constitutes 70-85% of Utah's water usage (Barlow, Chad et al., 2021).

The research delves into farmers' WTA water conservation payments, focusing on the adoption of water-conserving practices—a critical response to Utah's water crisis. The integration of economic theory, econometrics, and GIS technology enhances the robustness of the study, providing nuanced insights into the interplay of economic incentives and spatial dynamics. By emphasizing the utilization of RS data as an alternative to traditional survey methods, the research demonstrates the feasibility of cost-effective and scalable approaches for analyzing farmers' choices in spatially explicit contexts.

Interpreting the results reveals valuable implications. The estimated WTA payments serve as a pivotal metric, guiding the formulation of incentive-based policies crucial for sustaining Utah's agriculture and water resources. Notably, the findings offer nuanced insights into the economic thresholds of farmers, highlighting a key area where targeted interventions can yield maximal impact.

Beyond the immediate context of Utah, the research has broader implications for regions grappling with analogous water conservation challenges. As water scarcity evolves into a global concern, the methodology and insights presented here pave the way for informed policymaking and strategic interventions to secure the future of agriculture in water-stressed environments. This interdisciplinary approach serves as a blueprint for sustainable and adaptive water resource management strategies worldwide, emphasizing the power of collaborative research in addressing complex environmental issues.

While this study proposes an efficient approach to calculating farmers' WTA payments, the results would, in practice, merely be lower bounds to the actual WTA payments. A study comparing results from data collected through manual surveys and this method could provide more insight into the efficacy of the process. Again, the WTA and revenue loss results are for different years for different points due to stratified sampling. Hence, these results do not represent a single year. Nevertheless, this study initiates a new approach towards WTA calculation.

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