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Key Points:

- An input-output model is integrated into an agent-based model to capture dynamics between farmers and a city involved in a water transfer
- Long-term decline in crop water use corresponds with city growth rates while short-term decline corresponds with farmer discount rates
- Farmers' decision to sell their water rights results in increased unemployment and decreased output from other sectors of the rural economy

Supporting Information:

Supporting Information may be found in the online version of this article.

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Understanding Rural-to-Urban Water Transfers: An Agent-Based and Input-Output Modeling Approach

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Abstract Growing societal water demands and decreasing water supplies are straining the water available for communities in many basins. Once water supplies have been fully allocated and developing new water supplies is infeasible, the best option to meet growing water demands is often to reallocate water from rural agricultural water uses. Yet, the dynamics and implications of these rural-to-urban water transfers are poorly understood. Here, we integrate an agent-based model with an input-output model to capture the behavior of individual irrigators and examine how their water transfer decisions propagate through the broader rural economy and shape social dynamics. As a demonstration of our model, the rural community represents Alamosa County while the city represents the city of Denver, both located in Colorado, Unites States. We find that the greatest long-term decline in crop water use corresponds with higher city growth rates while the greatest short-term decline corresponds with larger farmer discount rates. As farmers sell their water rights to the City, economic activity from the crop production sector declines, causing unemployment in the crop production sector to increase and demand from the service sectors to decrease, which results in output declining in these economic sectors as well. Thus, a negative impact on the agricultural sector will cause some negative impact on other economic sectors, such as professional, health care, and recreational services. This research brings new insights that can be used to evaluate the socio-economic impacts of water transfers and shape policy to minimize potential negative externalities associated with water transfers.

Plain Language Summary Water scarcity has become a pressing issue as declining water supplies are increasingly unable to meet cities' growing water demands. To meet these growing demands, cities can transfer water supplies from rural communities by purchasing farmers' water rights. While these transfers meet urban water needs, it is not well understood how these water transfers impact the economy of the rural community. In this paper, we present a modeling framework that simulates rural-to-urban water transfers and quantifies the economic impact of this transfer on the rural community. In this demonstration of our model, the rural community represents Alamosa County while the city represents the city of Denver, both located in Colorado, Unites States. We find water transfers are driven primarily by farmer behavior in the short term, while the volume of long-term water transfers is more strongly determined by the urban population growth rates. When farmers sell their water rights to the city, they stop producing crops and no longer require additional workers. As a result, we show that unemployment rises and economic output decreases in the rural community across various sectors. With this modeling framework, we can identify strategies to better manage the economic impacts caused by rural-to-urban water transfers.

1. Introduction

Around the world, growing societal water demands and decreasing water supplies are straining the water available for both ecosystems and communities (Jury & Vaux, 2007). Reallocating water from existing users to new users is increasingly seen as the most viable option to meet new water demands in many areas (Marston & Cai, 2016). However, competition for limited water resources between growing cities and rural communities that utilize irrigated agriculture has often resulted in conflict between these urban and rural areas (Garrick et al., 2019; Marston & Cai, 2016). In Yemen, groundwater wells historically used by farmers were depleted in an attempt to meet the growing water needs of the city of Ta'iz (Riaz, 2002). In India, the transfer of water from agricultural regions to rapidly growing cities, such as Mumbai and Chennai, has led to political contestation and legal challenges (Punjabi & Johnson, 2019). Despite the social and political implications, rural-to-urban water transfers are likely to remain important in the future (Hommes et al., 2019), especially in places like the western United States (US) where water supplies have already been fully allocated in many basins and it is physically, politically, legally, and/or economically infeasible to develop new supplies. In the western US, irrigation for agriculture uses

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six times the water that is used by cities for public supply (Dieter et al., 2018). The cost paid by farmers to access irrigation waters and the economic value they derive from them are typically a fraction of the cost and value derived from water by urban municipalities (USDA, 2018a, 2018b, 2018c; Womble & Hanemann, 2020). This discrepancy in water use and value between agricultural communities and urban areas is why transferring water from water abundant farmlands to affluent urban areas is expected to increase in the western US over the coming decades (Garrick et al., 2019). Therefore, it is essential to understand the dynamics of water transferred from a rural to an urban community over time and the economic impacts of these transfers on the rural community in order to avoid the socio-political conflicts that have resulted from rural-to-urban water transfers around the world.

Under the Prior Appropriation Doctrine, which sets the allocation of water in much of the western US, water rights are not tied to land ownership; instead, the priority date of the water right determines a water user's priority to use available water (NSGLC, 2021). Many of the oldest (i.e., highest priority) and largest water rights are held by agricultural water users. As a result, there are several reports of urban areas in the western US buying up nearby farmer water rights and transferring these waters out of the rural community to meet increasing urban water demands, which is colloquially called "buy and dry" since these water transfers often lead to desiccated farmlands (Garrick et al., 2019). The Owens Valley water transfer to Southern California and the Crowley County water transfer to Aurora and Colorado Springs exemplify the "buy and dry" approach cities typically employ to secure water supplies (Libecap, 2009; Taylor et al., 1993). The rural farming community that exported the water is often left worse off due to loss of water, jobs, productivity, and, eventually, population (McColl, 2016; Petit et al., 2017). While the immediate outcome to the "buy and dry" approach is the desiccation of farmland, the secondary outcomes, such as broader unemployment and a decline in the rural economy, are not well understood and represent a gap in knowledge. In this study, we use a novel integrated modeling approach to address this knowledge gap, the socio-economic impacts caused by rural-to-urban water transfers.

Previous studies have applied various "bottom-up" modeling techniques, including optimization models (Howitt et al., 2012), multi-agent simulation (MAS) models (Berger et al., 2007; Klassert et al., 2023), and agent-based models (ABM) (Du et al., 2022; Matinju et al., 2023), to represent rural-urban water markets around the world. Specifically, these studies represent rural-urban water markets in California (Howitt et al., 2012), Chile (Berger et al., 2007), Jordan (Klassert et al., 2023), Texas (Du et al., 2022), and Iran (Matinju et al., 2023). These modeling approaches assess heterogeneous, micro-level information and define variables connected with local-scale actors but do not capture broader system dynamics (Eicken et al., 2021). To address this issue, these "bottom-up" models have been linked to biophysical models that constrain or influence micro-level decision-making (e.g., Du et al., 2022; Klassert et al., 2023). However, a modeling framework has not yet been developed to capture the interactions of rural-urban water markets and the economy of rural communities within the context of rural-to-urban water transfers. Previous research on water transfers has utilized policy, economic, or engineering approaches that only address one aspect of the challenge. The complex social, economic, and environmental implications of water transfers must all be considered, and solutions must be based on a comprehensive understanding of the human-water system (Marston & Cai, 2016).

In this study, we present an integrative modeling framework that captures the aggregated effects of micro-level farmer decisions on the rural economic system, and the influence of these meso-level economic impacts on individual decisions. We apply this modeling framework within the unique context of rural-urban water transfers. There have been several studies that integrate micro-level and meso-level economics and many of these studies have been applied to agricultural markets to represent the economy-wide impacts of farm-level decisions (e.g., Britz, 2008; Britz & Hertel, 2011; Parrado et al., 2020; Perez-Blanco & Standardi, 2019). In our framework, we chose to represent the rural economy using an economic input-output (IO) model, which has previously been integrated with micro-economic models within an agricultural context (Perez-Blanco et al., 2018). An IO model is a "top-down" model that can be easily parameterized using accessible, real-world data available at the meso-level. Furthermore, the IO model can uniquely capture the interdependencies of different entities through their economic interactions and it can also represent the resource requirements for each economic sector as physical quantities, including labor, land, and water. To represent the individual farmers in our framework, we used an agent-based model (ABM), which is a "bottom-up" modeling approach that has been applied in other studies to represent farm-level decisions (e.g., Berger, 2001; Lin et al., 2024; Ng et al., 2011). ABMs can capture the complex behavior of different autonomous actors with finer granularity, parameterized following economic or behavioral theory. Thus, ABMs can capture the heterogeneous decision-making of individual agents. By coupling these modeling approaches in our integrative modeling framework, we can trace individual farmer decisions through to community-level economic impacts in a way that has not been captured in other model representations of rural-urban water markets. While a handful of studies have integrated ABM and IO models for various applications, including carbon emissions (Andrade et al., 2010) and industrial symbiosis (Yazan & Fraccascia, 2020), the integration of an ABM with an IO model has yet to be utilized to examine the socio-economic impacts of water transfers from individual farmers, which is the novel contribution of this study.

In our modeling framework, we consider four types of entities: (a) farmers/water right holders (water exporters), (b) city (water importer), (c) rural economy, and (d) rural community. The farmers and the city are agents that are actively selling and buying water rights. Specifically, the city is a single agent i.e. buying and retiring the use of water rights for the farmer agents, resulting in a permanent transfer of water rights. The rural economy and community represent the environments in which these activities are occurring, which passively influence and can be impacted by the farmers' decisions. An economic IO model is needed to represent the rural economy because it captures the interdependencies of different economic sectors and the impacts of changes in one sector on to other sectors. The IO model also provides physical representations of labor, land, and water, which are the only physical representations within the modeling framework. Specifically, it represents the water used by each sector along with water available to be used by the crop production sector as physical quantities. Our representation of rural-to-urban water transfers is unique in that it captures both the micro-level, heterogeneous decisions of farmers and the meso-level considerations and impacts of the urban and rural communities, which are critical to properly represent the complex dynamics involved with water transfers. We can also identify the socio-economic conditions within the urban and rural communities that ultimately lead to broader unemployment and economic decline within the rural community, which is currently a knowledge gap in the literature.

In this study, we have developed an integrated ABM-IO framework to represent the behavior of individual farmers in a rural community, the socio-economic conditions that influence their decision to sell their water rights to an urban community, and the broader impacts of rural-urban water transfers. Specifically, we can capture how changes in crop production indirectly affect unemployment and economic output in other sectors of the rural economy. Our model is parameterized using data from Alamosa County, Colorado, which is used as a representative study area to ground our analysis. To demonstrate the novel capabilities and sensitivities of this integrated ABM-IO framework, which is the key contribution of this study, we designed illustrative scenarios to examine the influence of different urban growth rates and farmers' discount rates on the dynamics of water transfer. Although water transfer from the rural to urban study areas have been threatened for decades, water transfers have yet to occur so we cannot empirically validate an event that has not yet occurred. Given the limited data describing many rural-urban water transfer projects historically, our model aims to establish a modeling framework that can be used to explore and understand the socio-economic dynamics of rural-urban water transfers, using the study area to parameterize and ground our modeling framework in reality. Thus, our study answers the following two questions: (a) How does urban growth rate and farmers' discount rate influence the dynamics of water transferred from a rural to an urban community over time? (b) How does individual farmers' decision to sell their water rights impact the output from the crop production sector of the rural economy, as well as the total unemployment and economic output within the rural community?

2. Methods

2.1. Model Framework

Traditional modeling approaches that are based on a few simple rules or equations, such as differential equations or statistical models, are typically limited in their ability to represent micro-level processes or adaptive decision-making, which are important aspects of interdependent, socio-hydrologic systems (An et al., 2021). Agent-based modeling is a bottom-up approach that can capture the collective emergent behaviors with descriptions on an individual level, which make it a suitable tool for examining the heterogenous decisions of individual farmers to sell their water rights (Bonabeau, 2002; Zhao et al., 2013). Thus, we developed an ABM to capture the behavior of individual farmers in a rural community and the socio-economic conditions that influence their decision to sell their water rights to an urban community.

To capture the interactions between the individual farmers and the regional economy via the crop production sector of the economy, an economic input-output (IO) model is integrated with the ABM to develop an ABM-IO framework. The economic IO model is a top-down approach that represents the quantity of output from each sector of an economy in terms of its relationship to the output from the other sectors of the economy at the meso-

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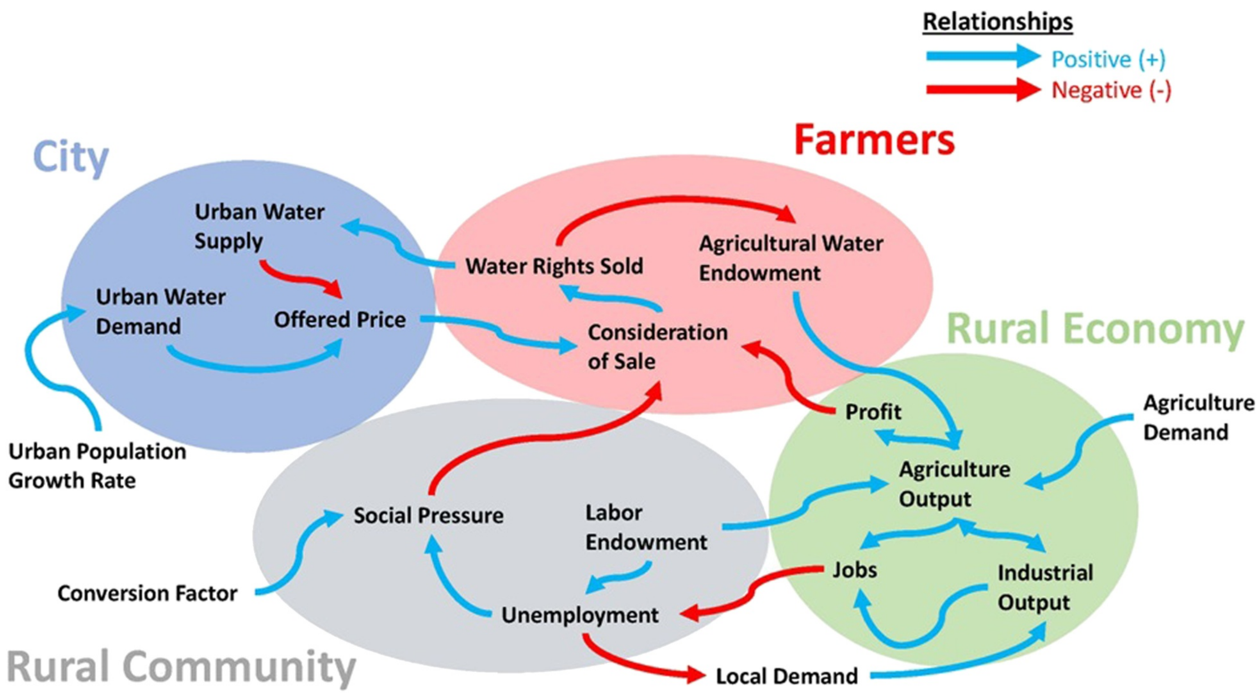

Figure 1. Causal loop diagram representing causal links among variables present in the four different sub-models of the ABM-IO framework (i.e., City, Rural Economy, Rural Community, and Farmers) where blue arrows represent a positive relationship between variables and red arrows represent a negative relationship between variables.

level (Leontief, 1970). Thus, by integrating an IO model into the Rural Economy sub-model of this modeling framework, we can capture the interdependency among the crop production sector and the other industries present within the rural economy as well as model the multisectoral feedbacks between the individual farmers and the rural economy as a whole. This feature allows us to capture how decisions made in the crop production sector impact unemployment and economic output in other sectors of the economy.

Our model was coded in Python using the Mesa package, developed by Kazil et al. (2020). Operating at an annual timestep, the ABM-IO framework is composed of City, Rural Economy, Rural Community, and Farmer sub-models, the linkages and composition of which are visualized in Figure 1. Specifically, this framework considers four types of entities: (a) water right holders/farmers (water exporter), (b) city (water importer), (c) rural economy, and (d) rural community. The farmers and the city are actors (agents) that are actively selling and buying water rights. Specifically, the city is buying and transferring the water rights of farmers to meet the growing water demands of the city. The rural economy and rural community represent the environments in which these activities are occurring, which passively influence the farmers' decisions. Each of these systems is described further in the following sub-sections, as well as in the Supporting Information S1, which follows the Overview, Design Concepts, Details, and Decision (ODD + D) protocol (Grimm et al., 2006; Müller et al., 2013). We also performed a sensitivity analysis for the ABM-IO modeling framework using a Python package called SALib (Herman & Usher, 2017; Iwanaga et al., 2022). We tested the influence of nine model parameters on three main model outputs. Once the model parameters were defined, 5,000 parameter samples were generated using the Latin hypercube sampling method available within the SALib package (Iman et al., 1981; McKay et al., 2000). These samples were generated within lower and upper bounds specified for each parameter. Next, outputs from the ABM-IO modeling framework were evaluated for each sample parameter. Then, we calculated the sensitivity indices for these nine parameters using the Delta Moment-Independent Analysis method available within the SALib package (Borgonovo, 2007; Plischke et al., 2013). The details and results of this analysis are included in the SI.

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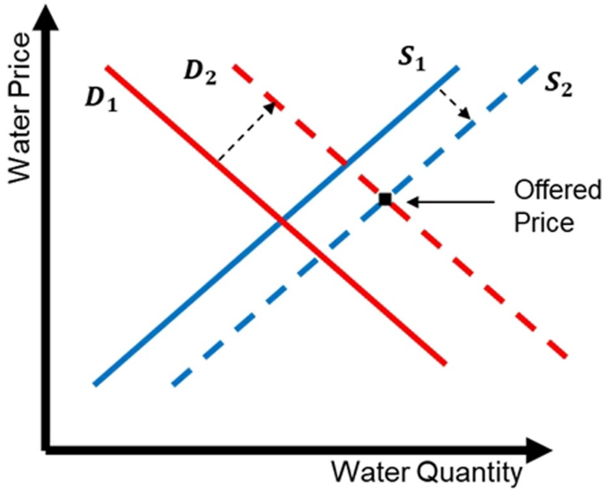

Figure 2. As the urban population grows, the initial water demand curve (D1) moves to a new position (D2). As the urban municipality purchases additional water supplies from the farmers, the initial water supply curve (S1) also moves to a new position (S2). The new optimal water price lies at the intersection of these new curves and this price will be offered by the City to the farmers for their water rights.

2.1.1. City Sub-Model

The City sub-model is designed to capture the water demand of a growing urban population, the water supply that the urban municipality has at its disposal, and the economic value placed on water by the City as it attempts to increase its water supply by purchasing water from farmers. The City uses microeconomics, specifically the law of supply and demand, to determine the value of Offered Price, which is defined as the price offered annually by the City to each of the farmers for their water rights. Assuming this system is in equilibrium, the optimal water price is found by calculating the value at the intersection of the urban water supply and urban water demand curves established for the City (McConnell et al., 2012). This assumption makes it impossible for the city to overpay for the water rights in our model setup. Specifically, the city will not pay more than their elasticity of demand would suggest or pay more than the farmers are willing to accept.

Before the start of the simulation, supply and demand curves are initially defined using price elasticities for water supply and demand, respectively, as well as an assumed initial optimal water price. Following the guidelines of McConnell et al. (2012), the water supply and demand curves were also assumed to be linear to reduce complexity while the price elasticities of supply and demand for water allocations were obtained from the literature and used to determine the slopes of these curves. Specifically, the values estimated by Zuo et al. (2016) for the price elasticities of water supply and demand were used in this study because it was one of the few studies to estimate values for both water supply and demand (0.42 and −0.57, respectively). Furthermore, the value estimated for the price elasticity of water demand lies within the range of values estimated for residential water demand in other studies: −0.38 by Sebri (2014), −0.41 by Dalhuisen et al. (2003), −0.51 by Espey et al. (1997), and −0.71 by Puri and Maas (2020). Furthermore, to better understand the parametric uncertainty within our analysis, we performed an uncertainty quantification where 5,000 samples of slopes for the water demand and supply curves were analyzed. While one model output was found to be more sensitive to the slope of the urban water demand curve than other parameters, other model outputs are more sensitive to other parameters. Therefore, the elasticity used to calculate the slope of the demand curve does not significantly influence all outputs from the modeling framework (see Supporting Information S1 for more details).

Beginning in the first year (timestep), the City increases water demand based on the increase in urban population that year. As urban water demand in the City increases, Offered Price will also increase. Similarly, the urban water supply will adjust based on the quantity of water rights bought from farmers at the end of the previous year (timestep). As the water supply available to the City increases, Offered Price will decrease. These adjustments in water supply and demand will cause an adjustment to the price offered to farmers for their water rights every year (see Figure 2). A boundary condition was also added to the city sub-model to ensure that the lowest price that the City could offer the farmers was $0.00/m^3, which indicates that the City has enough supply to meet demand at the current timestep and does not require additional supplies from the rural community.

2.1.2. Rural Economy Sub-Model

An economic input-output (IO) model is integrated into the ABM-IO framework, referred to as the Rural Economy sub-model, to capture the interdependency of agriculture and other rural economic sectors. Generally, the economy is divided into m distinct, interdependent sectors that each produce a quantity of output to meet a corresponding final demand each year (Leontief, 1970). To produce one unit (often a monetary unit) of economic output, each economic sector requires k factors of production that cannot themselves be produced, including labor, built capital (fixed assets), land, and water. Thus, the IO model calculates the annual economic output and factor use, including labor and water use, from each sector in physical, monetary, or mixed units (see Equations 1 and 2).

$$(\mathrm{I}-\mathrm{A})\boldsymbol{x}=\boldsymbol{y} \rightarrow \boldsymbol{x}=(\mathrm{I}-\mathrm{A})^{-1}\boldsymbol{y} \tag{1}$$

$$\boldsymbol{\phi} = \mathrm{F}\boldsymbol{x} \rightarrow \boldsymbol{\phi} = \mathrm{F}(\mathrm{I} - \mathrm{A})^{-1}\boldsymbol{y} \tag{2}$$

where,

A is the coefficient matrix ($m \times m$), F is the matrix of factor requirements per unit of output ($k \times m$), $\boldsymbol{y}$ is the final demand vector ($m \times 1$), $\boldsymbol{x}$ is the economic output vector ($m \times 1$), I is the identity matrix ($m \times m$), and $\boldsymbol{\phi}$ is the factor use vector ($k \times 1$).

These factors of production are only available in finite quantities and constrain production since factor use cannot exceed factor availability (referred to as factor endowments). Therefore, the IO model utilizes an objective function to minimize factor use while ensuring that factor use does not exceed availability and production still satisfies final demand (see Equation 3). If the required resource endowments are unable to meet the specified consumer demand, then no feasible solution would result for a scenario (Duchin & Levine, 2011). Additionally, each factor of production (labor, built capital, land, and water) has a corresponding price (wages, proprietor income, land rents, and water price, respectively), which must be paid to produce economic output (Duchin & Lopez-Morales, 2012; Lopez-Morales & Duchin, 2015). In this first iteration of the model, we assume that factor prices are fixed throughout the simulation period.

$$\text{Minimize } Z = \boldsymbol{\pi}'\mathrm{F}\boldsymbol{x} \tag{3}$$

$$\text{subject to } (\mathrm{I} - \mathrm{A})\ \boldsymbol{x} \geq \boldsymbol{y} \text{ and } \mathrm{F}\boldsymbol{x} \leq \boldsymbol{f}$$

where,

$\boldsymbol{x}$ is the economic output vector ($m \times 1$), $\boldsymbol{y}$ is the final demand vector ($m \times 1$), A is the coefficient matrix ($m \times m$), $\boldsymbol{f}$ is the factor endowments vector ($k \times 1$), F is the matrix of factor requirements per unit of output ($k \times m$), I is the identity matrix ($m \times m$), and $\boldsymbol{\pi}$ is the vector of factor prices ($k \times 1$).

In the Rural Economy sub-model of the integrated ABM-IO framework, the IO model was coded using the CVXPY package in Python, which was initially developed by Diamond and Boyd (2016) and further described by Agrawal et al. (2018). It is assumed that the final demand for Crop Production, one of the agricultural sectors, is composed entirely of demand for export while final demand for the service sectors (e.g., Professional, Educational, Health, Recreational, and Other Services) is composed entirely of local demand. These services are assumed to decline in proportion to employment declines in other sectors as unemployed rural residents will first decrease spending in these areas. Specifically, the baseline final demand from each of these service sectors was divided by the baseline number of people employed in the rural economy to obtain the different consumption rates associated with these sectors. Thus, based on these different consumption rates, final demand will decline as employment in the county declines. The final demand associated with the other economic sectors is assumed to be a combination of export and local demand.

At each timestep, the water endowment associated with Crop Production is reduced as farmers' water rights are sold to the City. Additionally, the final demand associated with Crop Production is also adjusted so that the quantity of water used by this sector is equivalent to the new water endowment, which results in a reduction of economic output for that timestep (year). The final demand associated with the service sectors is also reduced in response to reductions in jobs, resulting from the reductions in economic output from Crop Production. We assume that no changes in final demand occur because of changes in commodity prices since changes in local production would be unlikely to significantly affect commodity prices as these prices are determined by national or global market forces. Since the IO model interprets all changes to the final demand vector as changes in the number of sales rather than as changes in price, no sensitivity analysis was necessary for commodity price. Additionally, no sensitivity analysis was conducted for the parameters in the IO model since values representative of Alamosa County were obtained for these parameters. Thus, the outputs from the IO model are used to calculate Unemployment in the Rural Community sub-model (see Section 2.1.3), and the discount net present value of farmers' profit, which is input into the Farmers' sub-model (see Section 2.1.4). The farmers use this present value to assess the value of profit that they expect to earn using their water allotment to irrigate their cropland over a specified planning horizon. The farmers compare this value to the payment being offered to them by the city during the current year. This comparison captures that the value of the irrigation water has recurring benefits to the farmer, while the payment from the city only happens in the evaluation year. The city does not value water in the same way as farmers since the city's objective is to meet the water demands of its growing population. Therefore, the city does not need to estimate the present value of its water holdings because it is not critical to its strategy.

In this ABM-IO framework, the annual proprietor income generated by the crop production sector of the IO model represents the collective annual profit of farmers in that sector. Thus, to calculate the present worth of the farmers' annual profit, this annual profit is multiplied by the discount factor, shown in Equation 4 (Lindeburg, 1986), using several different discount rates described in Section 2.3 and a planning horizon of 20 years, which represents the time over which farmers consider benefits and costs. The 20-year planning horizon was selected because it is a typical loan period of Farm Service Agency (FSA) farm and ranch loans (FSA, 2023). The discount factor represents the value that the farmers place on the profit that they expect to receive during the 20-year planning horizon. If the discount factor is small, then the present worth of future returns will also be small.

$$\mathrm{DF} = \frac{(1+i)^t - 1}{i(1+i)^t} \tag{4}$$

where,

DF is the discount factor that annual profit is multiplied by to calculate present worth (unitless), i is the discount rate (unitless), t is the number of years into the future of each annual profit that is to be brought to present.

2.1.3. Rural Community Sub-Model

For this first iteration of the modeling framework, we chose to represent the Rural Community sub-model as an environment that is imposed on the individual farmers and influences their decisions, rather than as a collective because we wanted to establish the most basic dynamics between the city and farmers, which could be used as a foundation to build more complex dynamics. One of the concerns of rural residents in our study area is the economic impacts of water transfers on the rural community, which we represent in our model as unemployment. Each timestep, community-level unemployment is calculated in this sub-model using the labor endowment and number of jobs output from the Rural Economy sub-model. However, rural residents are also concerned about loss of culture and other complex concerns. Due to the uncertainty in parameterizing and quantifying such abstract variables, Unemployment within the rural community as a percentage of the potential workforce, a proxy for the economic health of the community, is considered the driver of social pressure. Other macro-level factors that could also affect unemployment are assumed to remain stable over the simulation period to isolate the effect of water sales.

Social Pressure (unitless) is calculated at each timestep n by multiplying the difference between current and initial unemployment by a conversion factor, CF (1/%; see Equation 5). Social Pressure is exerted on farmers not to sell their remaining water rights and increases as the discrepancy between community held expectations of unemployment and actual unemployment increases. Social Pressure is assumed to be zero at the beginning of the simulation before water sales occur (i.e., $\mathrm{Unemployment}_i$ serves as the baseline unemployment expectation). The conversion factor, CF, is initially assumed to equal 1.0 per unit of unemployment, but other values can be explored if social pressure is assumed to have a greater or lesser influence on farmer's decision-making.

$$\text{Social Pressure}_n = \mathrm{CF}\left(\text{Unemployment}_n - \text{Unemployment}_i\right) \tag{5}$$

2.1.4. Farmers Sub-Model

Irrigators holding water rights are represented as autonomous agents within the Farmers' sub-model of the ABM-IO framework. Expected utility theory drives farmer behavior within the Farmers sub-model. This commonly used behavioral theory assumes that all farmer decisions are driven by their desire to maximize their personal utility (Schrieks et al., 2021). To formulate this behavioral theory within the Farmers sub-model, we utilize a discrete choice modeling approach. Discrete choice models were initially derived from this concept of "utility maximization" for the purposes of representing qualitative human choice among distinct alternatives by McFadden (1974). In these models, each alternative has an associated utility function that consists of different attributes (McFadden, 1972). In the Farmers sub-model, there are two utility functions representing the choice to keep water rights and the choice to sell water rights, respectively. The incorporation of water rights is a purely binary outcome in this first iteration of the model because we are representing the "buy and dry" approach to rural-to-urban water transfers where the city offers the farmers a price for their water rights that is competitive with the present worth of the annual profit that the farmers expect to earn. While this approach is typical in the western United States, there have also been cases with leasing options or options where farmers sell just a portion of their water rights have been pursued. Future extensions of the model framework can examine these other types of rural-to-urban water transfers.

Following the principles of discrete choice modeling, the utility functions associated with each choice available to farmers are defined by assigning different weights (β) to the three attributes: Offered Price ($1000/ac) obtained from the City sub-model, Social Pressure (unitless) obtained from the Rural Community sub-model, and the present worth of Profit ($1000/ac) obtained from the crop production sector of the Rural Economy sub-model during timestep n. These β coefficients are used to define the utility functions associated with each decision available to the individual farmers (see Equations 6 and 7) (McFadden, 1972). The β coefficient for Offered Price ($\beta_{\mathrm{OP},i}$), has a negative value, meaning that as the price offered by the city to the farmers increases, the utility associated with keeping water rights decreases, $\mathrm{Utility}_{n,\mathrm{Keep}}$ (unitless), thereby making it less attractive for the farmer to keep their water rights (Mishra, 2014). The β coefficients for Profit and Social Pressure ($\beta_{P,j}$ and $\beta_{\mathrm{SP},j}$, respectively) also have negative values, which indicate that the higher the present worth of farmers' annual profit, or the higher the social pressure placed on farmers, these farmers get less utility from selling water rights, $\mathrm{Utility}_{n,\mathrm{Sell}}$ (unitless). There is an alternative-specific constant (ASC) associated with the choice to sell water rights, $\beta_{\mathrm{ASC,Sell}}$ (unitless), which represents other characteristics of this choice that are not made explicit within the utility function. This value is also negative, implying that this alternative is more negatively perceived than the choice to keep water rights (Mishra, 2014). The highest (least negative) utility associated with keeping or selling the water right is the preferred choice of the alternatives at that timestep.

$$\mathrm{Utility}_{n,\mathrm{Keep}} = \beta_{\mathrm{OP},i} * \text{Offered Price}_n \tag{6}$$

$$\mathrm{Utility}_{n,\mathrm{Sell}} = \beta_{P,j} * \mathrm{Profit}_n + \beta_{\mathrm{SP},j} * \text{Social Pressure}_n + \beta_{\mathrm{ASC,Sell}} \tag{7}$$

The utilities calculated by the Farmers sub-model reflect the preferences of the entire farmer population during each timestep, but to capture the preferences of the individual farmers, this discrete choice model utilizes random utility theory, which links the deterministic utility functions with a model of human behavior (Bierlaire, 1998). Specifically, this theory proposes that there is a probability distribution associated with a set of discrete choices and each individual agent will make their decision based on this distribution. Therefore, once the utilities are calculated at the end of each timestep to correspond with the choice to keep water rights and the choice to sell water rights, these utilities are then used to predict the probability that an individual farmer will choose to keep water rights, $P_{n,\mathrm{Keep}}$ (unitless), and the probability that they will choose to sell water rights, $P_{n,\mathrm{Sell}}$ (unitless), during that timestep (see Equations 8 and 9) (Bierlaire, 1998; McFadden, 1972). The Farmers sub-model generates a uniformly distributed random number between 0 and 1 for each farmer agent. If the value of the random number is greater than the probability calculated for keeping water rights during that timestep, then the farmer will sell their water rights, as shown in Equations 8 and 9.

$$P_{n,\mathrm{Keep}} = \frac{e^{\mathrm{Utility}_{n,\mathrm{Keep}}}}{e^{\mathrm{Utility}_{n,\mathrm{Keep}}} + e^{\mathrm{Utility}_{n,\mathrm{Sell}}}} \tag{8}$$

$$P_{n,\mathrm{Sell}} = \frac{e^{\mathrm{Utility}_{n,\mathrm{Sell}}}}{e^{\mathrm{Utility}_{n,\mathrm{Keep}}} + e^{\mathrm{Utility}_{n,\mathrm{Sell}}}} = 1 - P_{n,\mathrm{Keep}} \tag{9}$$

By calculating these probability distributions, we link the meso-level information obtained from the other sub-models to the micro-level, heterogeneous decisions of the individual farmers in this sub-model and capture the emergent behavior that results from these individual decisions. We used this simplified approach to differentiate farmer decision-making, but our framework is flexible such that more complex behavioral rules or theories could be used to differentiate farmers in future iterations of the modeling framework.

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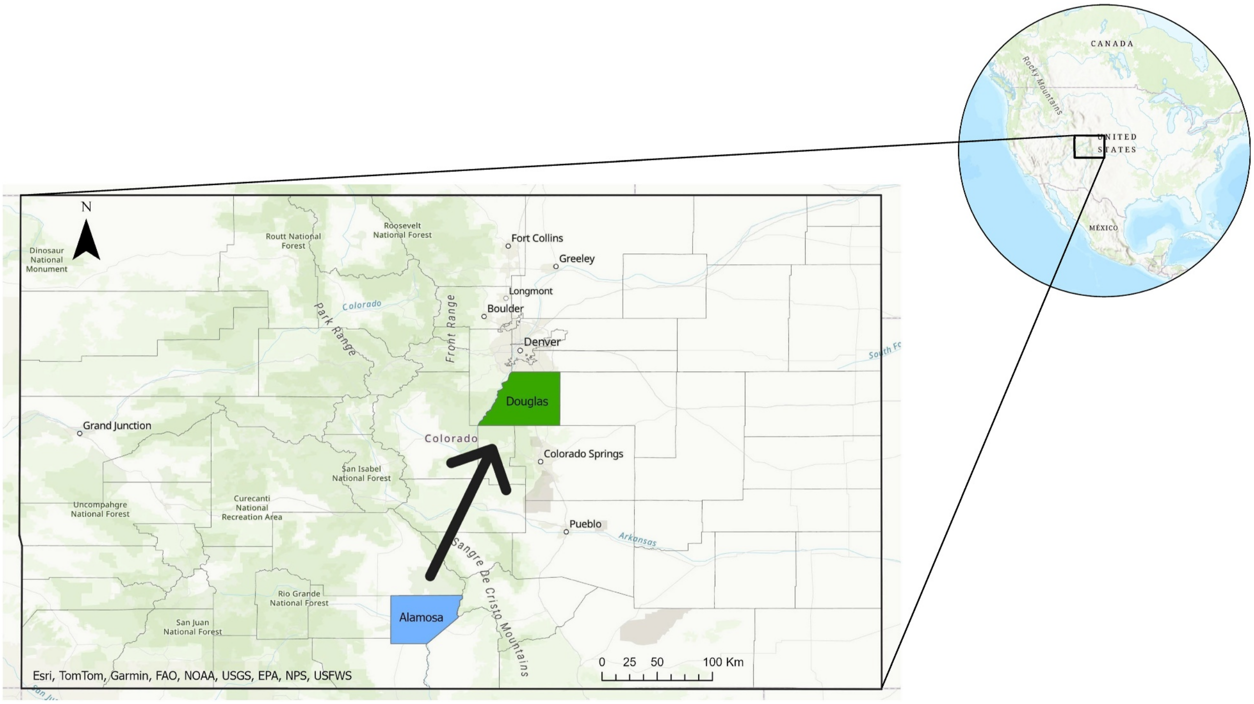

Figure 3. Map of Colorado, US. Counties are delineated in gray, with the proposed water transfer project being from Alamosa County (blue) to Douglas County (green).

2.2. Case Study and Data Requirements

We applied our ABM-IO framework to Alamosa County in Colorado, US to demonstrate our framework within the context of a real-world case study. Alamosa County, and the broader San Luis Valley upon which it resides, has faced repeated water transfer attempts by Douglas County, a rapidly growing urban community located in the metropolitan area of Denver, Colorado. Douglas County aims to buy irrigators' water rights and transfer these waters to meet the city's growing water demands (Sakas, 2022) (see Figure 3). In 2022, the community rejected a proposal by Renewable Water Resources to pump approximately 22,000 acre-feet (27 million m^3) of water annually to Douglas County from the San Luis Valley, a move that would have permanently retired groundwater wells in the area. This decision to reject the most recent water transfer offer came after significant social pressure and backlash. Water conservancy districts, many residents, and environmental groups in the San Luis Valley strongly opposed the project, arguing that they cannot afford a further loss of water. Despite this setback, like previous unsuccessful attempts over the past decades, leaders have not ruled out the possibility of future water transfers from the San Luis Valley (SLVEC, 2022). Thus, Alamosa County makes for an ideal case study to examine how water transfers from rural to urban communities could potentially impact a region in the long term.

Alamosa County is a rural community located in the San Luis Valley of Colorado, US with a population of 16,376 people and a total area of 1,870 km^2. Though Alamosa County receives less than 182 mm of precipitation annually (National Oceanic and Atmospheric Administration, 2022), it supports 28,000 ha of cropland due to an extensive irrigation network supplied by confined and unconfined aquifers as well as the headwaters of the Rio Grande. Irrigated crop production represents a significant component of the San Luis Valley's economy, especially alfalfa, potato, and barley crops (SLVDRG, 2022). Indeed, the farms in this region represent close to $400 million in market value of products sold (SLVEC, 2022), the barley grown in this region is one of the main suppliers for the Coors Beer Company (Brock & Hanson, 2023), and it is one of the largest potato producing regions in the United States (SLVEC, 2022).

Our model was parameterized with data from Alamosa County. The Rural Economy sub-model was parameterized using county-level, input-output data for Alamosa County, including sectoral intermediate demand, sectoral final demand, sectoral economic output, wages, proprietor income, labor, land, and water requirements. These data were for the year 2021 and come from the IMPLAN Group (2023). IMPLAN obtained input-output data from various federal agencies that conduct annual data collection and estimates, such as the US Bureau of

Labor Statistics (BLS), US Census Bureau County Business Patterns (CBP), and the US Environmental Protection Agency (EPA). In addition to obtaining data from different sources, IMPLAN also provided estimates for unavailable data, which are benchmarked against other data to verify accuracy. Additionally, we obtained sectoral built capital requirements for 2021 from the US Bureau of Economic Analysis (BEA) (BEA, 2022a, 2022b, 2022c). County-specific data on agricultural land use and land rents were obtained from the National Agricultural Statistics Service (NASS). All of the sectoral, input-output data obtained for Alamosa County were aggregated into 18 sectors following the guidelines provided by Miller and Blair (2009). Thus, this sub-model represents the rural economy as 18 distinct sectors (see SI), including three agricultural sectors and four service sectors, which are distinguished following the North American Industry Classification System (US Census Bureau, 2022).

In the Farmers sub-model, information provided by IMPLAN on the number of proprietors in the crop production sector was used to estimate the number of farmer agents present within the model (245). The specific attributes determined to influence farmers' decision-making were identified based on survey responses collected from farmers in Alamosa County, Colorado regarding the price at which they would be willing to make changes to their farming operations (Offered Price) and the income that they would have to obtain to keep their operations the same (Profit). Furthermore, it is also assumed that Social Pressure is an influential variable on farmers' decision making in Alamosa County since survey responses indicate that the health of the rural community does influence farmers' decision-making to a certain degree. Thus, the survey data obtained from farmers in Alamosa County was used in the Farmers sub-model to parameterize the utility functions associated with keeping and selling water rights. Additional details on the specific survey questions used in this analysis are included in the SI. We used the Python package Biogeme, along with the survey data collected from farmers in Alamosa County, to estimate β coefficients for Equations 6 and 7, which serve as input for the discrete choice model using maximum likelihood estimation (Bierlaire, 2023). Using Biogeme, a range of values were identified for each β coefficient, but only the range of coefficients estimated for Offered Price and Profit showed any robustness.

Thus, we also conducted a sensitivity analysis of the ASC and the β Coefficients for Offered Price, Social Pressure, and Profit (see SI). For this analysis, 5,000 samples were generated within specified bounds. These bounds were initially based on the range of coefficients estimated from the farmer survey data using the Biogeme Python package (Bierlaire, 2023) and then the lower bound was reduced to minimize the number of failed model runs. As a result, the ASC was bounded by -2.5 and -1.0, the β Coefficient for Offered Price was bounded by -1.0 and -0.1, the β Coefficient for Social Pressure was bounded by -1.5 and -0.1, and the β Coefficient for Profit was bounded by -1.5 and -0.1. The ASC and the β coefficients assigned to the variables for the scenario analysis were selected within these bounds. The β coefficients assigned to Offered Price and Profit (-0.52 and -0.72, respectively) were selected within the middle of their respective bounds. For the β coefficients associated with Social Pressure and the ASC, many different values were tested based on prior knowledge of the case study location and the resulting system dynamics of the ABM-IO framework were compared to the mental maps developed based on the causal loop diagram shown in Figure 1. The values ultimately selected for Social Pressure and the ASC were -1.02 and -1.87, respectively.

For the Rural Community sub-model, unemployment rates for Alamosa County were obtained from the US Bureau of Labor Statistics (2023). The initial value of community-level unemployment is set at 5.8%, which is the average of the monthly unemployment rates reported by the US BLS for Alamosa County in 2021 (US BLS, 2023).

Finally, we chose to represent the decision-making in the City sub-model as a competitive market. Since the 1930s, Colorado has implemented a water diversion project called the Colorado-Big Thompson Project in the northeastern region of the state (Howe, 2015). This project allows for water purchases in an open water market that is comparable to a real estate market. Given the long history of this market model for water in the state, it was reasonable to assume that a new water diversion project would follow a similar model of a competitive market. Thus, information on urban water use per capita was obtained from Denver's Water Efficiency Plan (2017). Population growth rates were obtained from the US Census Bureau (Korhonen, 2023) as was the initial population of the city, which was set to 700,000 people (the current population of the city of Denver) (US Census Bureau, 2023). Additionally, to determine the initial offered price used to establish the water demand and supply curves in the City sub-model, we examined a study by Womble and Hanemann (2020), which reported some actual market prices for water transfers around Denver, Colorado. Based on data obtained for 523 transactions, Womble and Hanemann (2020) found that, from 2008 to 2018, water prices ranged from \$198/acre-foot (\$0.16/m^3) to \$67,015/acre-foot (\$54.33/m^3) with a median price of $8,470/acre-foot ($6.87/m^3). Therefore, we selected an initial Offered Price of $1.40/m^3, which is within that reported range while still being competitive with the initial farmer income data reported by IMPLAN to ensure that the dynamics between the rural and urban community could be observed throughout the entire simulation period. Thus, we begin the model simulation where the offered price is acceptable to some farmers so that we can observe the socio-economic impacts of rural-to-urban water transfers in our scenarios.

2.3. Scenario Analysis

We compared different model scenarios to examine how urban growth rate and farmers' discount rate influence farmers' decisions and impact unemployment within the rural community. First, we assess how different annual urban population growth rates may impact the rural community over a 25-year simulation period, representing how the communities may be transformed in a single generation. We examined three different annual growth rates, 2%, 6%, and 10%, which are based on growth rates reported by the US Census Bureau for the city of Denver (2%) and some of the fastest growing cities in the western United States from July 2020 to July 2021 (Korhonen, 2023). Thus, while these higher growth rates are much less probable in the real world than the lowest growth rate, they are still within the bounds of plausibility and are appropriate for the purpose of examining the influence of urban growth on results produced by the model framework.

Second, we selected three different discount rates (2.5%, 15%, and 28%), which represent a range of discount rates plausibly used by farmers. The lowest plausible discount rate of 2.5% follows the US Office of Management and Budget (OMB) guidelines for benefit-cost analyses (OMB, 2022). However, previous studies indicate that farmers use significantly higher discounting when making decisions. Specifically, Duquette et al. (2012) surveyed a total of 293 farmers across two sample groups regarding their discounting behavior and, using a maximum likelihood model of the survey results, estimated that the farmers used a discount rate ranging from 28% to 43%. Meanwhile, Pannell et al. (2014) developed a model to assess the farm-level economics of conservation agriculture and applied discount rates ranging from 10% to 30%. Thus, we selected a middle discount rate of 15% and a highest discount rate of 28%, which is the minimum value recommended by Duquette et al. (2012), because the influence of discount rate on the discount factor becomes negligible at discount rates higher than this value.

3. Results

3.1. Sensitivity of Rural Community Outcomes to Farmer Discount Rate and Urban Growth

We find that crop water use declines in all scenarios but that the greatest long-term decline corresponds with higher city growth rates while the greatest short-term decline corresponds with larger farmer discount rates, which seems to be reflective of reality (see Figure 4). Specifically, in a review of 103 water reallocation projects from around the world, 80 of these projects cited “population growth” as a driver of reallocation (Garrick et al., 2019). Additionally, when irrigation water is distributed to farmers via shared infrastructure, all farmers selling their water rights is likely to be the eventual outcome since the fixed costs associated with maintaining the infrastructure is spread across all users. As more users sell their water rights, there are fewer farmers to share the costs, which increases the financial burden on the remaining irrigators and increases the likelihood that they will sell their water. At higher discount rates, farmers place less value on future crop profits and are therefore more inclined to accept a lower price for their water early in the simulation. Thus, the influence of annual profit on farmers' decision making becomes insignificant at higher discount rates and, in those scenarios, the dominant influence on farmers' decision making oscillates between the price offered by the city and social pressure from the rural community throughout the simulation period. Farmers value present gains much more than future gains, such as when a discount rate of 28% is used, which is why there is a steep decline in crop water use within the first 5 years, irrespective of how fast the city is growing. However, if farmers adopt a lower discount rate (i.e., 2.5%), then there is a more gradual initial decline in crop water use amongst all city growth scenarios. Regardless of which discount rate is applied, most of the farmers will sell their water rights in 25 years at the highest urban population growth rate (10%/yr), which implies an economic collapse of the crop production sector since output from this sector cannot proceed without access to a required resource.

While the chosen discount rate impacts the initial selling of water from farmers to the city, the outcome at the end of the 25-year simulation is very similar for both high and low discount rates. Conversely, the different urban growth rates do not lead to notable difference in water transfers (and thus a corresponding reduction in crop water use) initially. However, faster growth rates begin to exert pressure on the urban community to extend an ever-increasing

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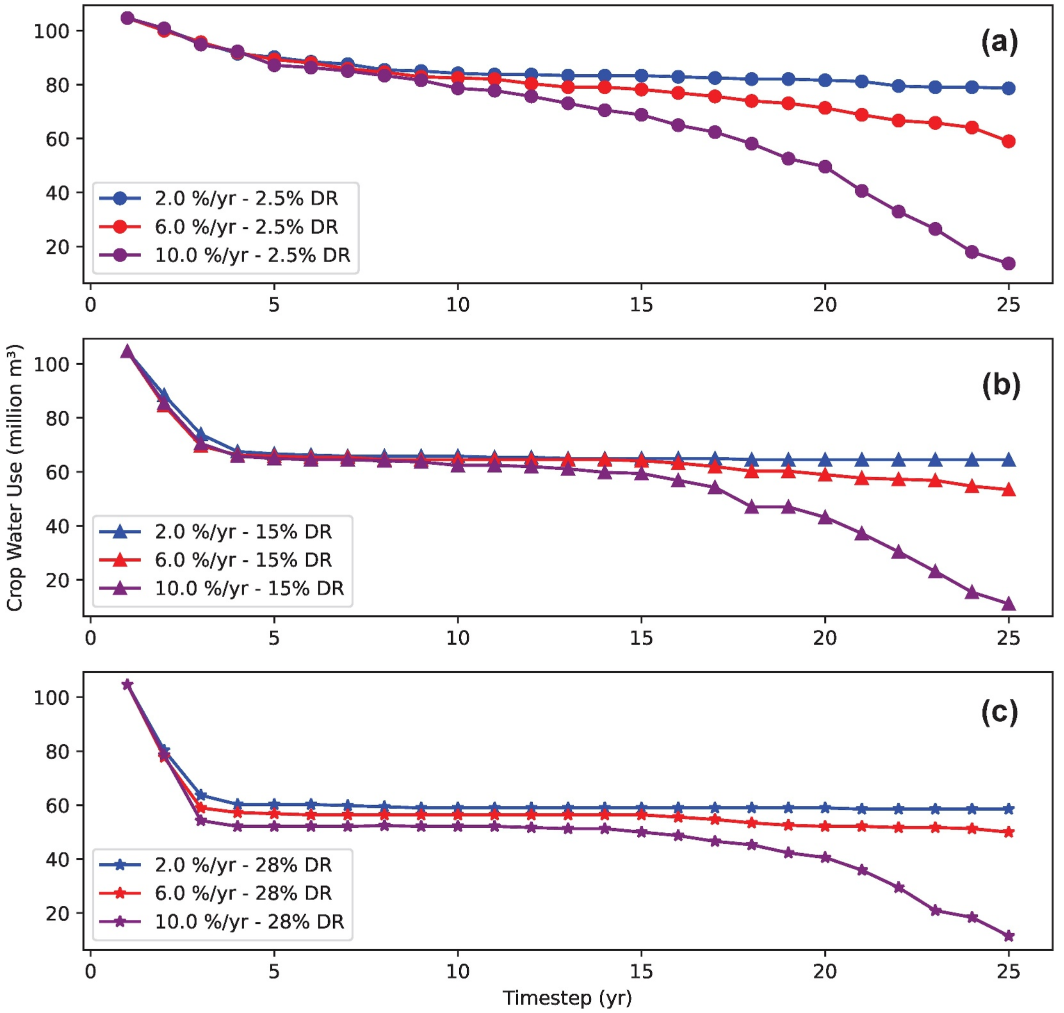

Figure 4. The quantity of water used (million m^3) by the crop production sector in the Rural Economy over the 25-year simulation period where (a) displays the results for each urban population growth rate (%/yr) using a 2.5% discount rate (DR), (b) displays the results for each growth rate (%/yr) using a 15% DR, and (c) displays the results for each growth rate (%/yr) using a 28% DR.

offer price to farmers, which entices more farmers to fallow their irrigated fields and transfer their water to the city. Figure 5 displays these long-term changes in offer price extended to the farmers by the city. At the highest urban population growth rate, almost all the farmers have sold their water rights by the end of the simulation period while at the lower urban population growth rates, sales in water rights decline in response to social pressure.

During the first few years of the simulation, the price offered to the farmers declines in response to the initial water right sales, which results in a sharp increase in water supply available to the City. At an urban growth rate of 2.0%/yr, the price offered to the farmers declines from 1.40 to less than 1.00 \$/m^3 over the 25-year simulation period. However, at an urban growth rate of 6.0%/yr, the price offered to the farmers increases threefold from 1.40 to over 4.00 \$/m^3, and at an urban growth rate of 10.0%/yr, the price offered to the farmers increases over eightfold, from 1.40 to close to 12.00 \$/m^3 since the ever-increasing urban water demand drives the water price higher. This trend in rising water prices seen in our model follows similar trends in water markets located in other regions of Colorado as reported by the Colorado Real Estate Journal (CREJ, 2020). The end results for each urban growth rate are about the same irrespective of the discount rate used by farmers since the price offered by the City to the farmers is not influenced by the discount rate used to calculate the present worth of farmers' annual profit.

Unemployment within the rural community follows a similar trend as crop water use (see Figure 6) demonstrating the strong connection between crop irrigation and the economic health of the rural community. Specifically, if

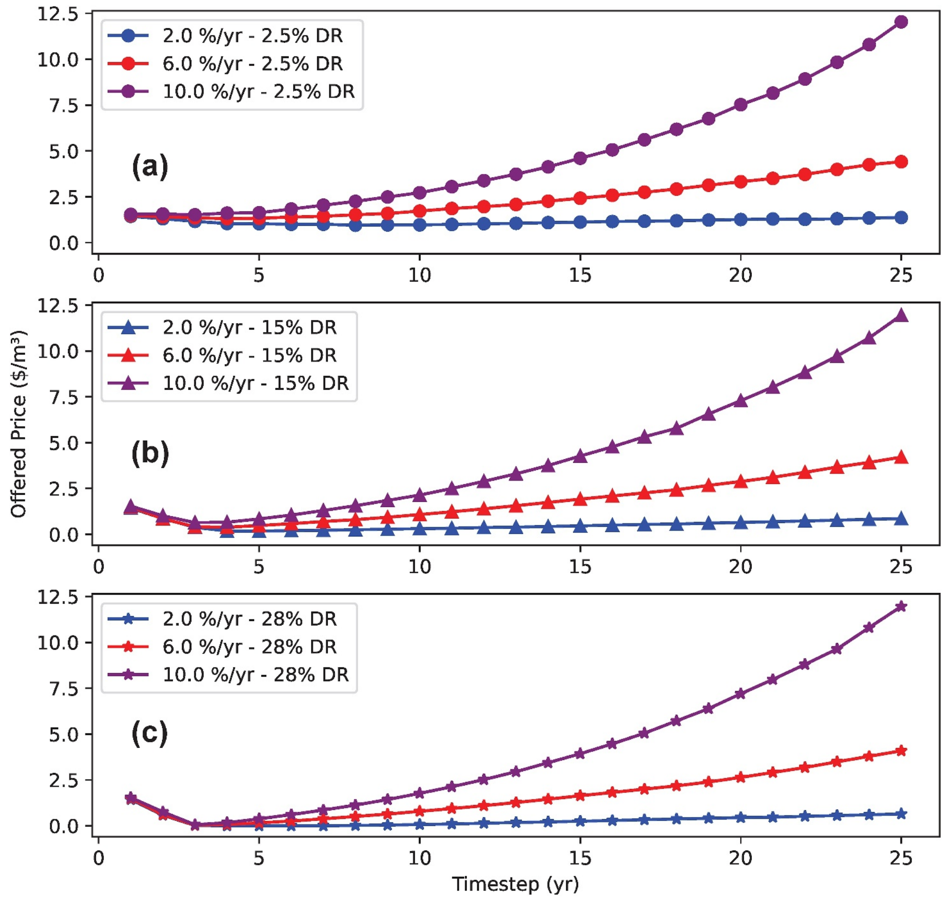

Figure 5. The price offered ($/m^3) by the City to the Farmers over the 25-year simulation period where (a) displays the results for each urban population growth rate (%/yr) using a 2.5% discount rate (DR), (b) displays the results for each growth rate (%/yr) using a 15% DR, (c) displays the results for each growth rate (%/yr) using a 28% DR.

water rights are rapidly sold, then unemployment rapidly increases. If few water rights are sold, then unemployment does not increase very much. The patterns observed for these two variables are the result of the same phenomenon. The final total unemployment rate within the rural community is about the same irrespective of the discount rate, although total unemployment initially rises much more sharply when a 28% discount rate is applied due to a fast selloff of farmer water rights and a corresponding hit to the rural economy.

At an urban growth rate of 2.0%/yr, the total unemployment in the rural community increases from 5.8% to around 8% at the end of the simulation period. At an urban growth rate of 10.0%/yr, however, the total unemployment in the rural community increases from 5.8% to around 14%. If enough farmers make the decision to sell their water rights, then the health of the rural economy will diminish unless there is a strong response from the rural community. However, a fast-growing city can offer farmers a financial incentive that will outweigh any social opposition to sell their water rights, resulting in a swifter decline of the rural economy.

3.2. Individual Farmer Decisions Have Community-Level Impacts

Every year, each farmer decides to keep or sell their water rights. The quantity of water being used by the crop production sector of the rural economy decreases throughout the simulation period as the number of farmers who have sold their water rights increases (see Figure 4). As a result of these sales, the total unemployment in the rural community also increases during the simulation period. Figure 7 compares the number of farmers who have sold their water rights to the total unemployment of the rural community for our middle scenario (6.0%/yr urban growth rate and 15% discount rate). As can be seen in Figure 7, approximately 40% of the initial water rights are sold within the first few years with few additional sales until around the fifteenth year, which is caused by a

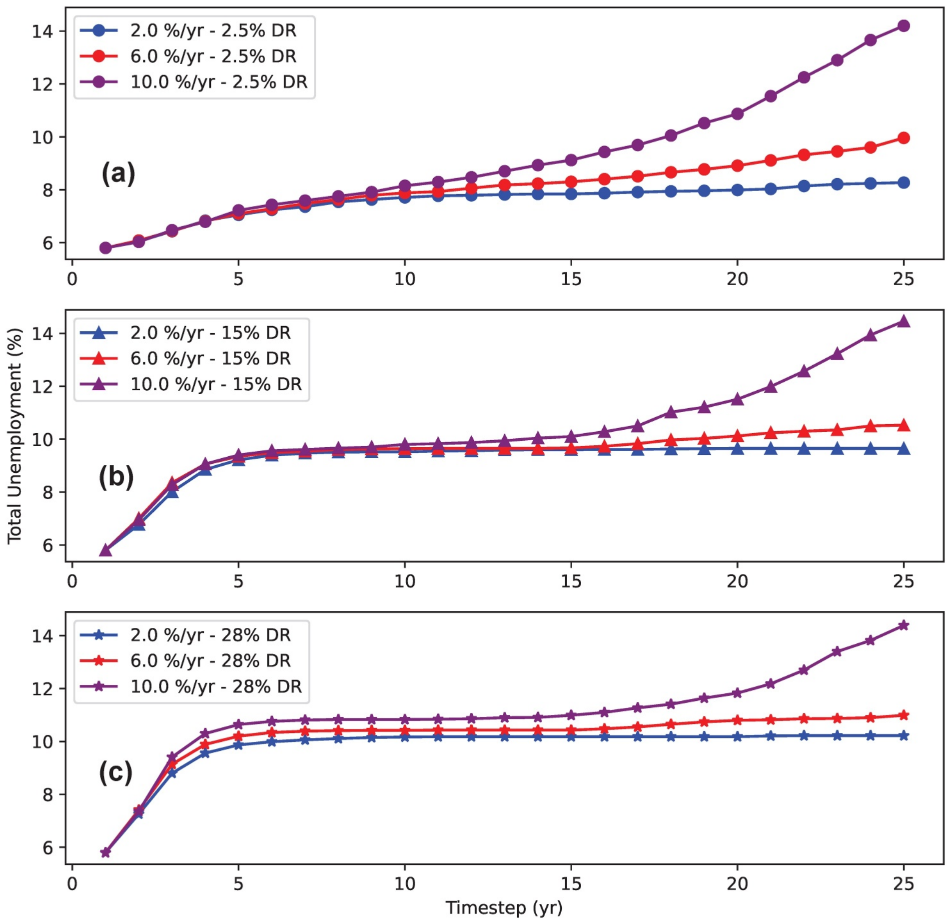

Figure 6. The total unemployment (%) in the Rural Community over the 25-year simulation period where (a) displays the results for each urban population growth rate (%/yr) using a 2.5% discount rate (DR), (b) displays the results for each growth rate (%/yr) using a 15% DR, and (c) displays the results for each growth rate (%/yr) using a 28% DR.

balancing loop present within the causal loop diagram (see Figure 1). This loop captures how water right sales are counteracted by social pressure from the rural community, which is driven by unemployment in the rural community. For example, around the fourth year of the simulation period, a threshold was reached where social pressure became more influential to the farmers than the price offered by the city, which resulted in an inflection point (see Figure 7). Furthermore, due to the linear relationship between different sectors' factor requirements and outputs represented by the IO model, the number of farmers who have sold their water rights and the total unemployment in the rural community follow similar trends during the 25-year simulation period. Thus, the decisions made by individual farmers to sell their water rights for personal financial gain impact the rural community as a whole and can ultimately cause the health of the rural economy to decline significantly.

While Figure 7 displays how the decisions of the individual farmers impact the rural economy as a whole, Figure 8 displays how the changes occurring within the crop production sector of the rural economy are influencing the other sectors of the rural economy. Specifically, as farmers sell their water rights to the City, economic output from the crop production sector declines. As a result of this decreasing agriculture output, unemployment in the crop production sector increases, which causes demand from the service sectors of the economy to decrease, which results in economic output declining in these sectors of the economy as well (see Figure 8). Thus, when the annual urban population growth rate is 6.0% (and a discount rate of 15%), almost 50% of the economic output from the crop production sector has disappeared by the end of the 25-year simulation period and, as a result, the economic output from the service sectors has decreased by as much as 5% (see Figure 8). Apart from the service sectors, economic output from the other sectors of the rural economy has collectively diminished 2% by the end of the of simulation period since all sectors of the economy are interdependent. Therefore, a decline in productivity

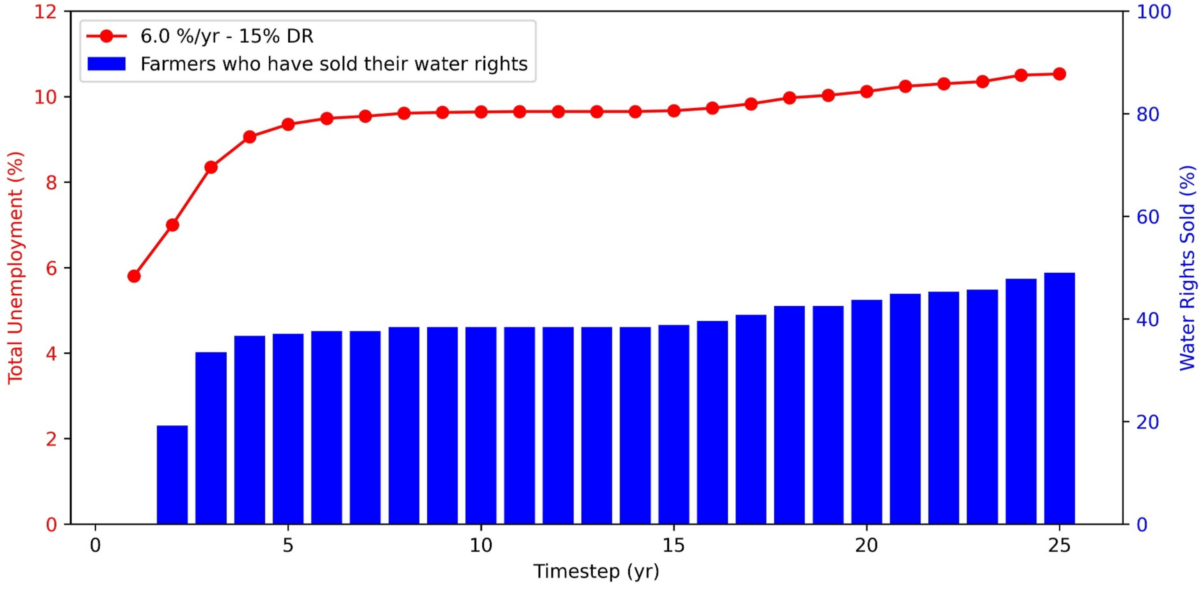

Figure 7. The total unemployment (%) in the Rural Community over the 25-year simulation period compared to the number of farmers who have sold their water rights during that period given a 6.0%/yr urban growth rate and a 15% discount rate (DR) used by farmers.

within one economic sector is not an isolated event and has indirect effects on other sectors of the economy, such as a decline in economic output and an increase in unemployment.

4. Discussion and Conclusions

In this study, we present a novel modeling framework that links a "bottom-up" ABM approach with a "top-down" economic IO model to capture the socio-economic dynamics and impacts of water transfers from rural communities to cities. We also conducted several scenario-based comparisons that examine how different urban growth rates affect the price offered by the city to farmers for their water rights and influence the decision made by individual farmers to sell their water rights, as well as how these individual decisions impact total unemployment

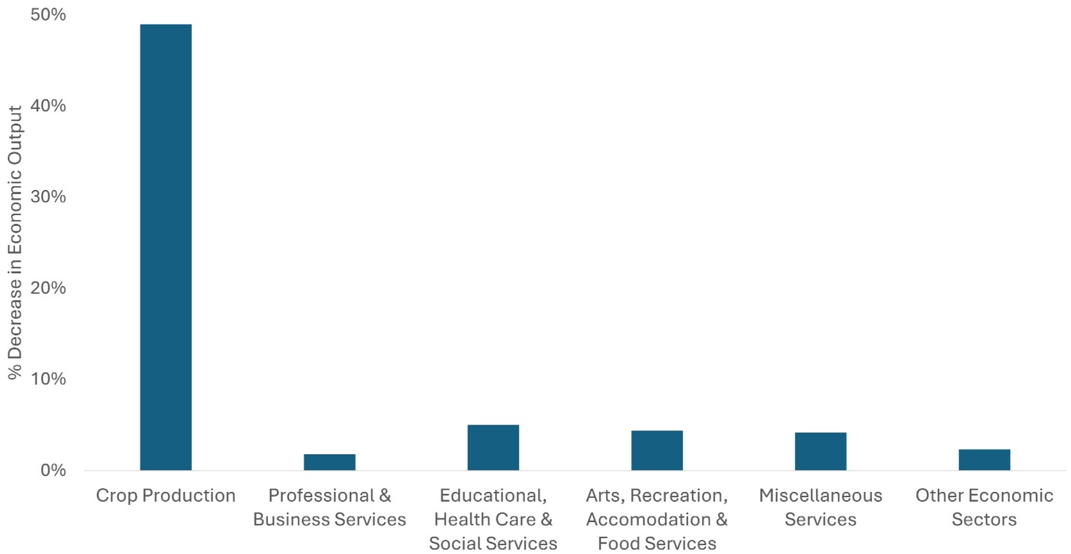

Figure 8. When annual urban population growth rate is 6.0% and farmers apply a 15% discount rate, the total decrease (%) in jobs after the 25-year simulation period from the following sectors: (1) Crop Production, (2) Professional & Business Services, (3) Educational, Healthcare & Social Services, (4) Arts, Recreation, Accomodation & Food Services, (5) Miscellaneous Services, and (6) the other 13 sectors of the rural economy combined.

and economic output in the rural community over time. Specifically, the sale of water rights results in the contraction of the crop production sector of the rural economy, which in turn results in a contraction of the service sectors causing jobs and economic activity to diminish across all sectors. Our model captures the general dynamics of rural-to-urban water transfers seen in the western US (Garrick et al., 2019). For example, Owens Valley experienced a period of rapid water right sales from 1922 to 1927 when the water rights of farmers were acquired by the city of Los Angeles, California. This period was followed by a period of very few water right sales until all the water rights were transferred to the city by 1932 (Libecap, 2009). Although the rural-to-urban water transfer of Owens Valley was completed in fewer years than any of the scenarios we examined in this study, our model was still able to capture these oscillations between periods of rapid sales and periods of few sales.

We attempt to balance model generalizability with realistic model parameterization, but this approach comes with its limitations. First, there is a level of structural uncertainty associated with the model outputs, which results from assumptions made when coupling these complex systems (Lin & Yang, 2022). While we took steps to minimize parametric uncertainty, such as using real-world data and literature to parameterize the modeling framework, this structural uncertainty has yet to be quantified. Second, migration and other adaptation dynamics were not fully accounted for in the current version of the model. The official government labor requirements reported by the crop production sector used to build the IO model, mostly likely do not include migrant or undocumented laborers. Therefore, the model results for the number of jobs and total unemployment are likely conservative. Additionally, if total unemployment in the rural community reaches a certain threshold, then it would be reasonable to assume that members of the rural community would start to move away or that the rural economy may adapt by encouraging the development of other sectors (e.g., solar energy generation), which could alter the dynamics between the rural economy and community. Third, this iteration of our modeling framework does not consider changes in water availability. Therefore, we do not examine how the dynamics of water transfers between the city and rural community differ under drought conditions, for example, Fourth, we assume that the city has completely exhausted all other water supply strategies and their only source of water is from the rural community. There will likely be alternative options, such as water reuse, desalination, or water conservation. While these options may be initially cost prohibitive or socially undesirable, they may become more attractive as purchasing water from holdout farmers becomes more expensive. Additionally, we assume that transaction costs in the market are implicitly included in the water price. That is, the water price represents net benefits to the farmer. We also assume the farmers all possess perfect knowledge of the price offered by the city. If information or power asymmetry existed between the city and the farmers, then an alternative modeling approach would assume a noncompetitive water market. Finally, our model represents an agricultural community that has other economic activity apart from crop production. Communities that are more reliant on agriculture would likely have even more pronounced negative economic outcomes than our case study and would be worth examining in future iterations. Thus, the scenario results generated by this first iteration of the modeling framework represent a basic relationship between a city and rural community, which we can use as a foundation to build more complex dynamics between the city and rural community. Future extensions of the model will address some of these limitations by adding a migration component, exploring more diverse behavioral theories and heterogeneity in farmer responses, and including other water supply sources and mechanisms for the city to compare water supply alternatives. Other possible model extensions are captured in the ODD + D protocol included in the SI.

Our ABM-IO framework provides new insight into the socio-economic conditions that influence farmers' decision to sell their water rights to a city, and the impacts of these decisions on the economic prosperity of the rural community. Specifically, this framework can allow us to anticipate the potential for rural economic collapse, which may arise because of dynamics between a city and a rural community. By understanding how and when these collapses occur, policy can be designed to limit how much water may be transferred to the urban community each year and mitigate the negative socio-economic impacts on the rural community. For example, the rural community could limit water sales per year, only sell actual water savings (see Grafton et al., 2018) resulting from a shift to more efficient irrigation technologies, and/or require the water exporter to establish a community fund to help offset the broader community harm caused by the water sales. These measures could be taken by the rural community to protect against the rapid sale of water rights, which limits adaptation time, and control the socio-economic transition caused by rural-to-urban water transfers. By utilizing extensions of this modeling framework to engage with stakeholders, we can identify strategies for sustainable water management in the western United States and other water-scarce regions.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The Python code and CSV data files used in the study are available at HydroShare via http://www.hydroshare.org/resource/9ead37e536894e2484e4909a04243810 under the Creative Commons Attribution CC BY (Amaya et al., 2024).

Acknowledgments
L.T.M. conceived the study. M.A. and L.T.M conceptualized the modeling framework and designed the scenarios that were examined in this paper. M.A. compiled the data that was input into the modeling framework and coded the modeling framework with notable assistance from C.Y.L. M.A. wrote the manuscript with substantial edits and comments provided by L.T.M. and C.Y.L. This material is based upon work supported by the National Science Foundation under Grant CBET-2144169 and the United States Geological Survey under Grant 13612182-Virginia. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) alone. Mention of trade names or commercial products does not constitute their endorsement by the U.S. Geological Survey.

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