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Modeling the Effects of Drought in Urban Economies Using Regional Input-Output Analysis

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

Aim: This research examines the economic impacts of drought severity and duration to interdependent production sectors in an urban catchment.

Methodology: We developed a dynamic water input-output model extension to analyze the drought vulnerability and resilience of economic sectors in an urban region. The model utilizes the North American Industry Classification System (NAICS), which encompasses 65 economic sectors in our regional analysis. The model is applied to a case study of the United States (US) National Capital Region, a predominantly urban region that is considered one of the major economic drivers of the US.

Results: Simulation results identify the critical economic sectors that experience the highest inoperability and economic losses as a result of water reduction schemes implemented during drought events. In the two scenarios studied (drought warning and drought emergency), sectors exhibit disproportionate levels of resilience and sensitivity to the magnitude and duration of water reduction. In each case, the economic loss and inoperability rankings of critical sectors differ due to differences in the quantity and value of the sectors' production outputs.

Conclusion: Observed data trends provide valuable insights for decision makers in formulating drought preparedness policies, water conservation programs, and short-term responses aimed to reduce water consumption in cases of emergency. The dynamic water reallocation I-O model developed in this study can be applied to other drought-prone regions and be used to generate insights on the economic consequences of drought, ecosystem thresholds, and water reallocation

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strategies that minimize the economic impacts of prolonged drought events and their ripple effects across sectors.

Keywords: Drought; water supply; reallocation; input-output analysis; economic sectors.

1. INTRODUCTION

The long-term sustainability of our water supply and demand is a subject of intensive global research. It is generally acknowledged that population growth, rapid urbanization, and threats of climate change exert tremendous pressure on the world's finite water supply. For example, a recent study has shown that based on 2005 water withdrawal rates, climate change will cause a third (1,100) of all counties in the United States to experience a high risk of water shortage by mid century [1]. Another study also projects that current economic and population growth rates will result in a 40% global water deficit by 2030 [2]. To address these problems, researchers underscore the need to develop diagnostic tools for planning adaptation strategies, especially during drought conditions [3]. These strategies are often regional or basin-wide in scale, and require water reallocation across sectors to minimize the net effect of the water crisis. Although it is recognized that modeling water scarcity is a complex undertaking, planning for demand management is considered a more effective mitigation measure than augmenting supply [4]. Increasing available water supply requires considerably higher infrastructure investments and often involves large-scale projects compared to managing water demand.

Water scarcity poses unacceptable economic risks that can impair growth and development. Within an economy, competition for limited water exists between agriculture and more highly valued sectors such as the manufacturing and service industries [5,6]. In regions characterized by water scarcity, policy makers face the challenge of designing an equitable water sharing plan across sectors [7]; however, the process often raises controversy due to the economic and social implications of water demand prioritization [8]. During drought events, water reallocation induces significant yet varying impacts on the operation and productivity of economic sectors. Sector responses to the magnitude, timing, and duration of water reduction exhibit high variability owing to the sectors' non-uniform sensitivity to water scarcity. For example, the effect of drought on agriculture is immediate and can be large-scale. The productivity and economic structure of the agriculture sector are highly sensitive to the onset and severity of drought but the sector's operation is able to recover with improving drought condition. Other sectors exhibit resilience to drought over the short-term but experience long-term effects on their economic productivity even as the drought condition improves.

Several methodologies have been proposed to analyze the impacts of drought and water reallocation on interdependent economic sectors. Seung et al. [9] applied computable general equilibrium modeling to demonstrate the effects of water trade-off between agriculture and recreation in Churchill County, Nevada. Velasquez [10] combined an input-output model extension to an energy model to estimate direct and indirect water consumptions across production sectors in Andalusia, Spain. The resulting model was used to determine the extent to which water availability may limit the economic growth of certain sectors. Zhao et al. [11] used input-output modeling techniques to account for the water footprint of consumer products in the water-stressed Haihe River basin in China. This footprint was used as a metric for assessing the compatibility of the economic activities in the basin with the concept of virtual water strategy for conserving water. Lennox and Dinkanova [12] developed a regional computable general equilibrium model to analyze the economic effects of water reallocation in Canterbury, New Zealand. Lopez-Morales and Duchin [13] applied a water input-output model to examine how government policies influence the adoption of alternative irrigation technologies. They found that policies can induce sustainable water withdrawals but prices of agricultural products rise by 5-8%. Banerjee et al. [14] developed an ecosystem services trade-off methodology to analyze the economic losses associated with drought, and applied this method to a case study of the Murray-Darling basin in southern Australia. Cazcarro et al. [15] constructed a multi-regional input-output model to assess water pressures, regional water footprints, and water trade-off among production sectors in Spain.

In modeling system interdependencies, the use of the economic input-output (I-O) model has gained popularity in recent years because of its practicality and relative ease of access to data [16]. The I-O model, which was developed by Leontief [17] and received the Nobel Prize in Economics in 1973, has been applied in numerous economic studies. The I-O model and computable general equilibrium extensions are useful in assessing the resilience of interdependent economic systems. Resilience is interpreted as the ability of a system to protect itself from external perturbations and eventually recover to its ideal state after being exposed to disruptive events [18,19]. For example, Rose and Liao [20] have demonstrated the role of resilience in counteracting the adverse effects of water service disruptions within an economic region.

Economic I-O models are traditionally used for modeling the ripple effects of changes in demand and supply patterns across interdependent sectors. Recently, there has been a rising trend in extending the I-O model for disaster risk analysis applications. Within the I-O literature, there are standard variables that capture the relevant measures of performance in an economic system (e.g., monetary units of production). In the proposed model, we seek to develop performance measures to characterize and quantify different types of subsystem interdependencies – building on and supplementing the economic-based interdependencies typically used in I-O models. Haimes and Jiang [21] expanded the Leontief model to analyze situations where interdependent systems are unable to satisfy the needed demand for their outputs. Santos [22] explicitly integrated the use of economic I-O accounts to model the effect of infrastructure inoperability and its ripple effects to interdependent economic sectors.

This paper focuses on the economic consequences of drought to urban water users. When water availability plays a critical role in an urban economy, reductions in water supply can result in serious disruptions to the over-all economic activities of the region. In this study, we develop a regional input-output model extension to estimate the inoperability and economic losses that are incurred across interdependent sectors over time during prolonged periods of drought. It was applied to a study of the impacts of water demand management in the United States (US) National Capital Region (NCR), a predominantly urban region that is considered an economic driver in the US.

2. METHODOLOGY

2.1 Water Input-Output Extension Model

The water I-O model presented in this study is an extension of the inoperability input-output model (IIM). It was developed to capture the effects of water supply reduction scenarios to interdependent economic sectors. The IIM is a transformation of the traditional I-O model that utilizes a dimensionless variable called *inoperability*, which is a measure of the inability of a sector to meet demands for its output. Inoperability values range between 0 and 1; an inoperability value of 0 corresponds to the undisrupted state of affairs, a value of 1 corresponds to total system failure. The IIM was recently developed to describe the dynamic recovery of interdependent industry sectors that are exposed to a disruptive event. To date, this dynamic IIM (DIIM) has been expanded and applied in various fields [23-25]. The dynamic formulation of the IIM serves as the basis for the proposed *Water Input-Output Extension Model*. The formulation is as follows:

$$\mathbf{q}(t) = \mathbf{q}(t-1) + \mathbf{K}[\mathbf{A}^*\mathbf{q}(t-1) + \mathbf{c}^*(t-1) - \mathbf{q}(t-1)] \quad (1)$$

Where $\mathbf{q}(t)$ and $\mathbf{q}(t-1)$ correspond to the inoperability vector at time t and $t-1$, respectively; $\mathbf{A}^*$ is the interdependency matrix that represents sector interdependencies and can be obtained directly from published I-O data, $\mathbf{K}$ is the resilience coefficient matrix, and $\mathbf{c}^*(t-1)$ is the vector of demand perturbations at time $t-1$. For simplicity, we assume in the subsequent case study that the demand perturbations are negligible, as the focus of the analysis will be on the changes in the inoperability, $\mathbf{q}(t)$ and $\mathbf{q}(t-1)$. This is a reasonable assumption since user demand for water is expected to remain at pre-drought levels despite the reduced supply (i.e., this has to be contrasted with the concept of "forced" demand reduction where consumers have to curtail their demand for water or look for other sources to compensate for shortfalls). Furthermore, the formulation for the resilience matrix are based on Lian and Haimes [23], which is reproduced here as follows:

$$k_{ii} = \frac{1}{T(1-a_{ii}^*)} ln\left(\frac{q_i(0)}{q_i(T)}\right) \quad (2)$$

The term a_{ii}^* corresponds to the diagonal elements of the $\mathbf{A}^*$ matrix, which are pre-specified constants defined previously in Eq. (1). Hence, the above recovery parameter (k_{ii}) only depends on the initial condition (*t*=0) and a terminal condition (*t*=*T*). Note also that it is assumed that recovery is achieved when $q_i(T)$ has reached a negligible level relative to the initial inoperability $q_i(0)$. Hence, the model in Eq. (1) depends primarily on the assessment of the inoperability $q_i(t)$, which will be the subject of subsequent discussions.

In the inoperability vector $\mathbf{q}(t)$ in Eq. (1), each element denoted by $q_i(t)$ corresponds to the inoperability of sector *i*. The effects of reduced water availability on the production output of a sector can be estimated by computing the ratio between the water input requirement (w_i) and the total production output (x_i) of a particular industry sector i. The resulting ratio, w_i/x_i, gives information regarding the portion of a sector's output that is dependent on water input. Furthermore, this ratio provides insights on how a regional shock to the water supply can be modeled as an inoperability to a particular sector *i*. For simplicity, this ratio is assumed to be invariant of time for similar reasons as discussed earlier (i.e., the "as planned" water dependency of a sector to support its production is assumed to remain at pre-drought levels). The water input requirement (w_i) and total production output (x_i) data for each sector can be obtained from the regional economic accounts as published by the US Bureau of Economic Analysis [26].

Furthermore, we introduce a time-dependent drought multiplier, $d(t)$, to describe the extent to which a drought scenario disrupts water supply availability. This multiplier ranges between 0 and 1. A value of 0 is the ideal case where the water supply remains in an undisrupted state, while a value of 1 refers to the maximum disruption. The multiplier $d(t)$ measures the water availability disruption caused by a drought scenario on sector production. For each period *t*, we assume that the disruption, $d(t)$, affects the entire regional economy; hence, it does not include a sector-specific subscript, *i*. Nevertheless, this disruption trickles across the different industry sectors after being multiplied with the water dependency ratio (w_i/x_i). Collectively, this formulation creates a sector inoperability that is a function of both the industry sector *i*, as well as the period *t*, as follows:

$$q_i(t) = \frac{w_i}{x_i} d(t) \quad (3)$$

Relating Eq. (3) to (1) for every iteration *t* generates the inoperability of each industry sector. The time-dependent disruption function, $d(t)$, is assumed to be a characteristic of the drought scenario being considered. In the case study section (Section 2.4), we will describe how this function is simulated for several scenarios. Hence, by tracking the resulting inoperability of each sector, we are also able to estimate the associated economic losses triggered by the disruption in water supply. The *Water Input-Output Extension Model* builds on the dynamic inoperability formulation presented in Eq. (1) and includes a function that updates the level of inoperability based on the prevailing level of water availability disruption.

$$q_i(t) = \begin{cases} (w_i/x_i)d(t), & d(t) > 0 \\ q_i^{DIIM}(t), & d(t) = 0 \end{cases} \quad (4)$$

Note that $q_i^{DIIM}(t)$ is the i^{th} element of the vector $\mathbf{q}(t)$ as formulated in Eq. (1). The new formulation in Eq. (4) realistically captures the progression of a sector's inoperability depending on the magnitude of the disruption to water availability. The inoperability of a particular sector is directly proportional to the disruption, $d(t)$, and the proportionality constant happens to be the sector-specific water dependency ratio, w_i/x_i. Furthermore, consider a time sequence where $d(t-1) > 0$ and $d(t) = 0$. Based on Eq. (4), the inoperability at time t will be $q_i^{DIIM}(t)$, which implies that a sector's inoperability does not quickly recover to the ideal value of 0 (i.e., full production capacity). This makes sense, as the effect of restoring water availability does not instantaneously reinstate a sector's production to its full capacity. As implied in Eq. (2), the length of time to achieve full recovery ultimately depends on a sector's interdependency with other sectors (as captured by a_{ii}^*), as well as its inherent resilience (as captured by k_{ii}).

On the other hand, the economic loss incurred by a sector *i* results from its failure to operate at its normal state (i.e., the undisrupted condition, where sector inoperability is 0). When a sector experiences some level of inoperability, this causes the sector to have a temporary loss in its ability to deliver the normal level of production. Hence, for every period *t*, economic loss is calculated as the product of the inoperability $q_i(t)$ and the economic output of the sector for this period. This approach implicitly assumes that the economic output of sector *i* can be averaged over the drought horizon *T*. This assumption is reasonable because the drought horizons considered in the case study span significantly long periods (e.g., 90 days), which in effect minimizes the effect of daily production output fluctuations.

2.2 Database Sources

This section provides a discussion of the data sources for the US NCR case study. Based on recorded history and projections [27], this economic region is vulnerable to shortfalls in the delivery of essential services, such as water supply disruptions triggered by droughts. These disruptions in turn can lead to degraded production levels. In order to quantify the impact of reduced sector production levels on the regional economy, economic data (such as input requirements, commodity outputs, and income statistics, among others) for each regional sector are collected and assembled from different sources.

2.2.1 Sector classifications

This paper adopts the data collection methodology using the North American Industry Classification System (NAICS). The Regional Input-Output Multiplier System (RIMS II) uses an aggregated version of the detailed sector classification, composed of 65 sectors (see Table 1). The standardized sector classification method allows users to yield comparable results when applying the same model to another region.

2.2.2 Input-output matrices

The Bureau of Economic Analysis (BEA) publishes the annual I-O matrices for the 65-sector decomposition as depicted in Table 1. This methodology is coupled with RIMS II to provide a useful framework for evaluating economic interdependencies [28]. These data are available from BEA for the nation as a whole, each state, metropolitan regions (using the U.S. Census definitions), and counties.

2.2.3 Gross domestic product

Gross Domestic Product (GDP) consists of final consumption, other than those used as intermediate production inputs to the 65 endogenous sectors. As such, GDP is also interpreted as the value of final uses (or consumptions), which includes personal consumption expenditure, gross private domestic investment, government purchases, and net foreign exports (i.e., difference in exports and imports) [16]. GDP data is also available for all states and metropolitan areas within the United States.

2.3 Virginia Drought Classification

This study adopts the Virginia Drought Severity Classification System. Drought conditions are typically determined using indices that are calculated based on parameters such as rainfall, stream flow, groundwater levels, and temperature. In the United States, drought classification is based on a variety of indices, for example, the Palmer Drought Severity Index (PDSI). Normal conditions are indicated by a PDSI value of zero; worsening drought conditions are indicated by increasingly negative PDSI values. In the Commonwealth of Virginia, drought conditions are monitored by the Virginia Drought Monitoring Task Force (DMTF). The DMTF uses four drought indicators (Table 2): precipitation, stream flow, groundwater level, and reservoir storage. Each indicator is assigned four drought severity categories: normal, watch, warning, and emergency. The water reductions are enforced when at least two of these indicators are in the same drought category.

2.4 Case Study

The US National Capital Region (2012 population of 5.9 million) was selected for this case study due to its high population density, urbanization, and economic activity. It includes the Washington District of Columbia, 11 counties and 6 cities in Virginia, 5 counties in Maryland, and 1 county in West Virginia (Fig. 1). The region is a major economic driver in the US and includes seven of the highest-income counties in the country [29]. It is also home to several federal agencies, professional service sectors, research facilities, and large-scale data centers.

Table 1. Sector classification adopted in the US NCR case study

Sector	Description	Sector	Description
S1	Farms	S34	Pipeline transportation
S2	Forestry, fishing, and related	S35	Other transportation and support activities
S3	Oil and gas extraction	S36	Warehousing and storage
S4	Mining, except oil and gas	S37	Publishing industries (includes software)
S5	Support activities for mining	S38	Motion picture and sound recording
S6	Utilities	S39	Broadcasting and telecommunications
S7	Construction	S40	Information and data processing services
S8	Food and beverage and tobacco	S41	Federal Reserve banks and credit
S9	Textile mills and textile product mills	S42	Securities, commodity contracts, and investments
S10	Apparel and leather and allied	S43	Insurance carriers and related activities
S11	Wood products	S44	Funds, trusts, and other financial vehicles
S12	Paper products	S45	Real estate
S13	Printing and related support	S46	Rental and leasing services
S14	Petroleum and coal products	S47	Legal services
S15	Chemical products	S48	Miscellaneous professional and scientific services
S16	Plastics and rubber products	S49	Computer systems design and related services
S17	Nonmetallic mineral products	S50	Management of companies and enterprises
S18	Primary metals	S51	Administrative and support services
S19	Fabricated metal products	S52	Waste management and remediation
S20	Machinery	S53	Educational services
S21	Computer and electronic products	S54	Ambulatory health care services
S22	Electrical equipment, appliances, and components	S55	Hospitals and nursing and residential care facilities
S23	Motor vehicles, bodies and trailers, and parts	S56	Social assistance
S24	Other transportation equipment	S57	Performing arts, spectator sports, and museums
S25	Furniture and related products	S58	Amusements, gambling, and recreation
S26	Miscellaneous manufacturing	S59	Accommodation
S27	Wholesale trade	S60	Food services and drinking places
S28	Retail trade	S61	Other services, except government
S29	Air transportation	S62	Federal government enterprises
S30	Rail transportation	S63	Federal general government
S31	Water transportation	S64	State and local government enterprises
S32	Truck transportation	S65	State and local general government
S33	Transit and ground passenger transportation	*From:*	[26]

Table 2. Virginia drought categories

Drought Indicator	Drought severity level[a]			
	Normal	**Watch**	**Warning**	**Emergency**
Precipitation (October-September data)	>85th percent	<85 percent	<75 percent	<65 percent
Stream flow (7-day average compared to historic levels)	>25th percentile	10th-25th percentiles	5th-10th percentiles	<5th percentile
Groundwater level (compared to historic data)	>25th percentile	10th-25th percentiles	5th-10th percentiles	<5th percentile
Reservoir storage	>120 days	90-120 days	60 to 90 days	<60 days
Water reduction[b]	NA	0-5%	5-10%	10-15%

[a]*The state of Maryland uses the same four indicators for classifying drought severity, however, the water reduction goals are slightly different for each drought category.*
[b]*at least two indicators must have the same drought severity level to trigger water reduction*

Fig. 1. Map of the US National Capital Region. The study area includes: The Washington District of Columbia, 11 counties and 6 cities in Virginia (Alexandria, Arlington, Clarke, Culpeper, Fairfax, Fairfax City, Fauquier, Falls Church, Fredericksburg, Loudon, Manassas, Manassas Park, Prince William, Rappahannock, Spotsylvania, Stafford, and Warren), 5 counties in Maryland (Calvert, Charles, Frederick, Montgomery, Prince George), and 1 county in West Virginia (Jefferson)

A regional I-O database was constructed for contiguous US NCR counties and cities based on BEA economic estimates. Using assumptions extrapolated from Table 2, the Water I-O Model was implemented for two scenarios (i.e., warning and emergency). We recognize that a myriad number of drought scenarios can be potentially considered for analysis (e.g., various combinations and durations of watch, warning, and emergency scenarios). For a more streamlined discussion and demonstration of the *Water Input-Output Extension Model*, we focused specifically on the two subsequent drought scenarios, both with a 90-day recovery timeline. This recovery assumption is consistent with historically observed droughts in the region [27].

2.4.1 Scenario 1: drought warning

For a drought warning to occur, it is assumed that at least one of the following conditions applies: streamflow level falls within the 5^{th}-10^{th} percentiles, groundwater level falls within the 5^{th}-10^{th} percentiles, and precipitation is below 75%

of normal. In addition, it is assumed that the reservoir level is expected to deplete in the next 60-90 days. With these conditions, a drought watch occurs where available water supply is reduced by about 5-10% of the normal consumption requirement levels.

This scenario considers a 90-day horizon that comprises three periods:

- Period 1: Water reduction starts at Day 0 with $d(0) = 0\%$ and worsens until water reduction peaks at 60 days with $d(60) = 5\%$. We simulated the intermediate values of the disruption function $d(t)$ to describe the transition from $d(0) = 0\%$ to $d(60) = 5\%$.
- Period 2: Approximately one week in the 5% water reduction condition
- Period 3: Water reduction condition is improved until recovery is achieved at t=90 days, or $d(90) \approx 0\%$. The disruption function $d(t)$ was simulated from a value of 5% at the beginning of Period 3 until it reaches a level that is reasonably close to 0% at the end of the 90-day horizon.

2.4.2 Scenario 2: drought emergency

Based on Table 2, an emergency can happen if either stream flow or groundwater level falls below the 5th percentile, or precipitation is below 65 percent of normal. Furthermore, it is assumed that reservoir level will deplete in less than 60 days. When these conditions are met, a drought emergency occurs where available water supply is reduced to within 10-15% of the normal consumption levels.

For comparability with the drought warning scenario, a 90-day horizon with three periods also is considered. The process of simulating the intermediate values of the disruption parameter $d(t)$ is similar to Scenario 1 and is not repeated here for brevity. The assumed periods are as follows:

- Period 1: Water reduction starts at t=0 and worsens until peak reduction value is reached at t=45, or $d(45) = 15\%$.
- Period 2: Approximately two weeks in the 15% water reduction condition
- Period 3: Water reduction condition is improved until recovery is achieved at t=90 days, or $d(90) \approx 0\%$.

3. RESULTS AND DISCUSSION

3.1 Scenario 1: Drought Warning

For the drought warning scenario, the top ten sectors with highest inoperability values (Fig. 2), in decreasing order, are: Mining (S4), Utilities (S6), Textile mills and textile product mills (S9), Apparel and leather and allied products (S10), Electrical equipment, appliances, and components (S22), Educational Services (S53), Accommodation (S59), Support activities for mining (S5), Federal general government (S63), and Furniture and related products (S25). In general, sector inoperability remains unchanged until day 5, then starts to increase as the water reduction increases, remains relatively steady as the water reduction is maintained at 5%, and finally decreases very rapidly up to about 20 days since the water supply is gradually returned to normal levels. An exception is exhibited by the Accommodation sector, whose inoperability continues to increase even as the water supply is kept steady at its peak 5% reduction, before it starts to decrease when the water supply begins to gradually improve.

For the same scenario, the top ten sectors with highest economic losses (Fig. 3), in decreasing order, are: Real estate (S45), Educational services (S53), State and local government (S65), Utilities (S6), Federal government enterprises (S62), Federal general government (S63), Accommodation (S59), Other services (S61), Broadcasting and communications (S39), and Computer systems design and related services (S49). The cumulative economic loss for these sectors is US$ 18 million, a sixth of which is incurred by the Real estate sector and a tenth by each of the sectors: Educational services, State and local government, and Utilities. The Real estate sector incurs the largest loss because it has a relatively significant water dependence ratio coupled with the fact that it is one of the largest contributors to the gross regional product [26].

It can also be inferred from Fig. 3 that economic losses are negligible up to about day 10 when losses begin to rise more rapidly. Note also that the onset of peak economic loss (where economic loss starts to plateau) for each sector is different, indicating varying levels of economic resilience over time to water reduction levels. In contrast with droughts that have previously affected other less urban regions in Eastern US [27], the “Farms” sector (denoted by S1 in

Table 1) did not place in the 10 critical sectors generated by the economic loss ranking. This observation is intuitive since the National Capital Region considered in this case study was limited to the highly urbanized counties in the three states (Maryland, Virginia, and West Virginia). Hence the resulting economic loss to the Farms sector is relatively negligible as this sector is not a primary contributor to the gross regional product of the study area.

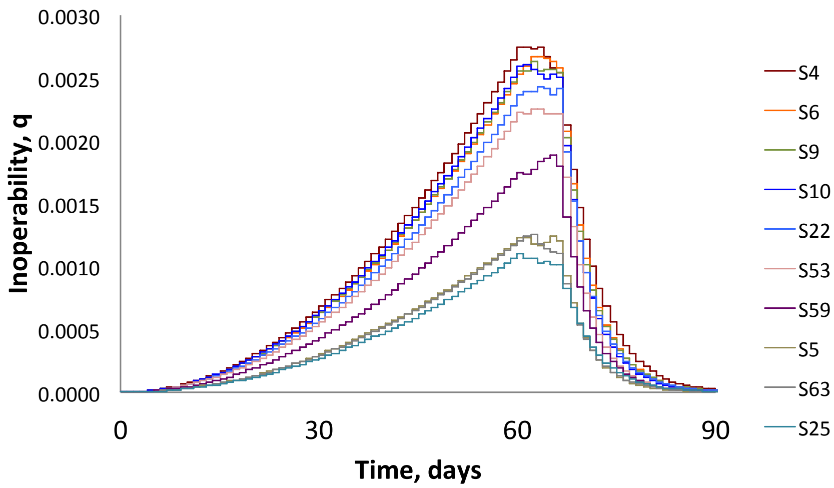
3.2 Drought Emergency

The top ten sectors with highest inoperability values (Fig. 4), in decreasing order, are: Utilities (S6), Mining (S4), Apparel and leather and allied products (S10), Textile mills and textile product mills (S9), Electrical equipment, appliances, and components (S22), Educational Services (S53), Accommodation (S59), Pipeline transportation (S34), Support activities for mining (S5), and Federal general government (S63). The Utilities sector exhibits the most dramatic increase in inoperability. Its peak inoperability is between three to ten times the inoperability of the nine other sectors, and ten times its inoperability in the drought warning scenario. However, its recovery is also the most rapid when water supply begins to improve. Generally, sector inoperability returns to normal around the 75-85 day mark. The increased inoperability of the Utilities sector under the drought emergency scenario is likely attributed to its failure to deliver its product output (e.g., services such as domestic water and sewage collection and treatment) to other sectors of the economy as a result of water reduction. The inoperability of the Pipeline transportation sector increases to its peak value at day 65, approximately 5 days after the water supply begins to improve, before it starts to dissipate to the pre-drought level. This phenomenon can be explained as a ripple effect, where the indirect effects of other sectors (as captured by a_{ii}^* in Eq. (2)) exceed the inherent resilience (as captured by k_{ii}) of the affected sector. Furthermore, other sectors that are not necessarily shown in Fig. 4 (i.e., there are a total of 65 sectors) may have also contributed to the indirect inoperability of the Pipeline transportation sector prior to its full recovery to the pre-drought level. It can be seen from Fig. 4 that the inoperability for the most affected sector (Utilities) reaches a peak value close to 0.025 (i.e., 2.5% inoperability, or equivalently a 97.5% reliability). This is followed by a cluster of sectors that have reached peak inoperability values near 0.01 (i.e., 1% inoperability, or 99% reliability). These inoperability values may not sound alarming at first; nevertheless to put these numbers into perspective, a six-sigma quality compliant system requires a *maximum* failure rate of 3.4 parts per million (or an inoperability value of 0.0000034).

The top ten sectors with highest economic losses (Fig. 5), in decreasing order, are: Utilities (S6), Real estate (S45), Educational services (S53), State and local government (S65), Federal government enterprises (S62), Federal general government (S63), Accommodation (S59), Other services (S61), Computer systems design and related services (S49), and Retail trade (S28). The cumulative economic loss for these sectors is US$ 73 million, 25% of which is incurred by the Utilities sector and 14% by the Real estate sector. Generally, it takes 10-20 days from the onset of water reduction before the sectors experience rapid economic loss. Similar to the drought warning scenario, sectors continue to experience economic losses even after water supply begins to improve, albeit at a slower pace, before the economic losses plateau. The total economic loss for this particular drought emergency scenario appears to be in the same order of magnitude as other historically observed droughts in the region [27].

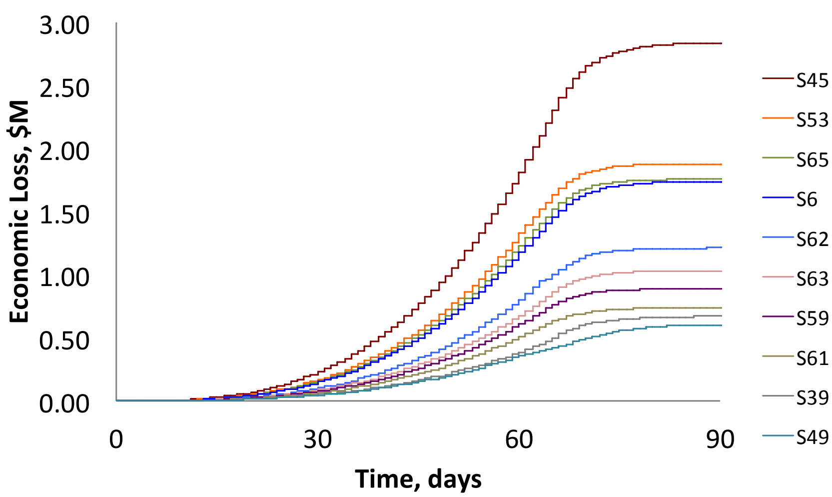
3.3 Implications to Water Demand Management and Prioritization

For the studied scenarios (drought warning and drought emergency), drought severity induces a wide variability in sector resilience to the magnitude and duration of water reduction over the drought timeline. Depending on the drought severity, this variability can indicate disproportionate economic losses and inoperability among production sectors when uniform water reduction is imposed in the entire region. The level of resilience across sectors is also not proportional to the degree of water reduction, as indicated by the changes in critical sector rankings (e.g., Utilities sector) in the two simulated scenarios. Furthermore, although sector inoperability increases (i.e., production is disrupted) earlier in the drought timeline, there is a delay in the onset of the sector's economic loss. These trends provide water and industry managers valuable insights in formulating adaptation strategies that can minimize the magnitude of sector losses and production disruptions over time.



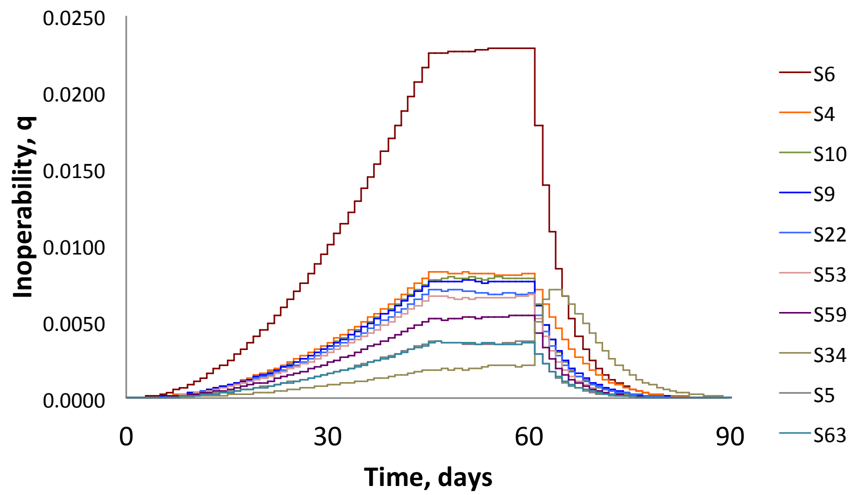
S4 Mining, except oil and gas
S6 Utilities
S9 Textile mills and textile product mills
S10 Apparel and leather and allied products
S22 Electrical equipment, appliances, and components
S53 Educational services
S59 Accommodation
S5 Support activities for mining
S63 Federal general government
S25 Furniture and related products

Fig. 2. Ten most critical sectors in terms of inoperability



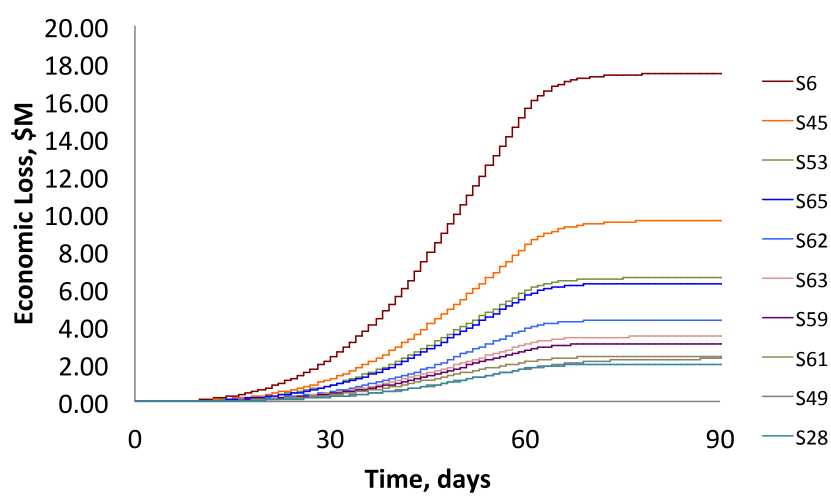
S45 Real estate
S53 Educational services
S65 State and local general government
S6 Utilities
S62 Federal government enterprises
S63 Federal general government
S59 Accommodation
S61 Other services, except government
S39 Broadcasting and telecommunications
S49 Computer systems design and related services

Fig. 3. Ten most critical sectors in terms of economic loss (Total loss = $18M)



S6	Utilities
S4	Mining, except oil and gas
S10	Apparel and leather and allied products
S9	Textile mills and textile product mills
S22	Electrical equipment, appliances, and components
S53	Educational services
S59	Accommodation
S34	Pipeline transportation
S5	Support activities for mining
S63	Federal general government

Fig. 4. Ten most critical sectors in terms of inoperability



S6	Utilities
S45	Real estate
S53	Educational services
S65	State and local general government
S62	Federal government enterprises
S63	Federal general government
S59	Accommodation
S61	Other services, except government
S49	Computer systems design and related services
S28	Retail trade

Fig. 5. Ten most critical sectors in terms of economic loss (Total loss = $73M)

For the scenarios considered in the case study, the model yields different rankings of critical sectors depending on the importance given to the economic loss and inoperability measures. The magnitudes of the production output for different sectors vary considerably in the National Capital Region (as in any other region); hence, different rankings of sector criticality were depicted from Figs. 2 through 5. It should be emphasized that when non-uniform water reallocation is considered as a strategy for managing water demand, reallocation should not be based solely on the economic loss or inoperability ranking. Water reduction in a sector will have ripple effects to other sectors that provide inputs or accept outputs from this sector; consequently, these affected sectors also will experience changes in their inoperability and economic loss profiles.

4. CONCLUSIONS

In this paper, we demonstrate the adverse effects of water availability disruptions to interdependent sectors of a regional economy. We present a water input-output model extension for estimating the consequences incurred across interdependent sectors during periods of drought. The model features two distinct measures of risk for identifying critical interdependent economic sectors namely, *economic loss* and *inoperability*. Economic loss reflects the monetary worth of the reduced production for an industry sector. In contrast, inoperability identifies the critical sectors not necessarily on the magnitude of the financial loss, but rather on the 'normalized' loss of each sector as a proportion of its total production output. This dynamic model extension features versatile functions that allow the evaluation of intervention strategies implemented during the drought timeline that can influence sector recovery as water supply conditions evolve. The US NCR case study demonstrates that economic sectors exhibit varying resilience, both in terms of productivity and economics, to water distribution schemes that are implemented during drought events. Simulation results identify the critical sectors that are sensitive to slight changes in water reduction schemes. Observed data trends also provide valuable insights for decision makers in formulating drought preparedness policies, long-term water conservation programs and short-term responses aimed to reduce water consumption in cases of emergency. The dynamic water reallocation I-O model developed in this study can be applied to other drought-prone regions, and be used to generate insights on the economic consequences of drought, ecosystem thresholds, and water reallocation strategies that minimize the economic impacts of prolonged drought events and their ripple effects across sectors. This paper contributes to advancing the current state of research in the development of drought impact analysis models. Robust analytical models are critical in developing drought management strategies especially in vulnerable regions that are expected to experience increased drought frequencies as a result of our changing climate patterns. These tools are particularly useful in arid regions; they can facilitate the formulation of policies that minimize the direct and indirect impacts of drought across sectors. Ultimately, evaluating the effects of droughts to interdependent industry sectors can enhance the capability of a region to better allocate its scarce resources in times of emergency.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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