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Editorial

Water Use in Irrigation and Technical Efficiencies

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IRRIGATION

(Tetila EC et al., 2020) DMUs encounter significant variances in their production capabilities as well as the features of the manufacturing environments in which they operate. As a result, DMUs are likely to see significant disparities in production and efficiency (Kamilaris Aet al., 2018). The conventional literature, on the other hand, suggests that DMUs have identical technological capabilities and only differ in terms of inefficiency. This paper creates an analytical framework with random factors to account for variation in production possibilities and production environment characteristics. We use this framework to investigate differences in irrigation output elasticity across DMUs and how these differences influence: irrigation water use efficiency (IWUE), a non-radial input-oriented approach that isolates and measures the efficient use of the irrigation input; technical efficiency, which radially measures the efficient utilisation of all inputs; and irrigation withdrawal shadow prices. We discovered that IWUE and technical efficiency averaged 72.6% and 83.6%, respectively, and shadow costs averaged $77.5 per million gallons of irrigation water, with considerable regional differences (Mamdouh N et al., 2021).

(Brunelli Det et al., 2020) .Given increased water demand and expected precipitation reductions due to climate change, efficient water resource management has become a key issue in US agriculture. Several regions in the United States are still experiencing serious drought and water shortages, endangering the agricultural sector's survival. Because of increased climate variability, such as rising temperatures and decreased precipitation, irrigated agriculture is now undertaken in water-stressed conditions. As a result, irrigated agriculture competes directly with other water uses such as domestic, industrial, and hydropower. (Suto J et al., 2022)For some years, evidence in the United States has been accumulating that indicates a link between climatic unpredictability and the demand for secondary sources of water, such as irrigation (Vega J et al., 2019). Rising temperatures, according to one primary explanation, increase crop evapotranspiration rates, rapidly diminish soil moisture, and so increase crop water demand. The changing temperature and precipitation patterns have directly resulted in changes in farming practises and resource consumption, as well as an increased reliance on irrigation. With 62.4 million acres of land under irrigation, the agricultural sector is currently the second largest consumer of water resources in the United States, accounting for around 115,000 million gallons per day (Lee G et al ., 2021).

It is expected that demand for agricultural water use will continue to climb, putting a strain on the system. In the short run, increased irrigation can be expected to mitigate the detrimental consequences of climatic variability. However, the longer-term potential for enhanced irrigation practises to tackle agricultural sector water concerns may shrink due to water constraint and competition with other sectors of the economy (Zou X et al ., 2017). In order to increase production, the emphasis will have to move to sustainable water resource management and land-use intensification (Mamdouh N et al., 2021).

As a result, given agriculture's sensitivity to secondary water sources in the face of water shortage, an examination of irrigation systems and how efficiently they are implemented in agricultural productivity has become increasingly important. Water use efficiency is defined in hydrology literature as the ratio of harvested biomass to water consumed to obtain a particular yield. The rate of carbon uptake per unit of water lost has also been established as a measure of water use efficiency. Water use efficiency, on the other hand, is frequently used in economic research to refer to the effectiveness of applied irrigation and the ratio of the minimal feasible water utilised to observed water usage associated with a particular level of output, when other inputs and technology are held constant. The agriculture sector in the United States is a large consumer of water resources, accounting for around 115,000 million gallons per day in 2010, or 38% of total fresh water withdrawals. Climate change, typified by rising temperatures and frequent and severe droughts, has heightened the demand for alternative water sources for agriculture. This has generated questions about the efficiency of present irrigation practises among policymakers and stakeholders alike. In turn, sustainable water resource use necessitates the use of updated and current water management and irrigation systems to optimise irrigation scheduling and application. Water must also be regarded as an economic good in order to become a marketable commodity, as market development can improve water's allocative efficiency. Finally, regulations that favour conservation, such as water harvesting, precision irrigation techniques, and deficit irrigation, are required for sustainable water use. (Parsons R et al., 2020).

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