

EFFICIENCY OF DRIP IRRIGATION SYSTEMS IN IMPROVING WATER USE IN ARID REGIONS

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Abstract

Water scarcity is one of the most serious challenges affecting agricultural productivity in arid and semi-arid regions. This study examined the efficiency of drip irrigation systems in improving water use, crop yield, soil moisture retention, and economic returns under arid climatic conditions. The results showed that drip irrigation substantially reduced total irrigation water application compared with conventional surface irrigation while maintaining better moisture availability in the root zone. Drip-irrigated plots recorded higher water productivity, improved application efficiency, and better crop yield performance, indicating that precise and localized water delivery can reduce water losses through evaporation, runoff, and deep percolation. The findings also showed that drip irrigation helped control soil salinity by maintaining more stable moisture conditions and reducing salt accumulation near the active root zone. Economic analysis further indicated that although drip irrigation requires higher initial investment, the system produced greater net returns due to reduced water use, improved yield, and better resource efficiency. Overall, the study confirms that drip irrigation is an effective and sustainable irrigation strategy for improving agricultural water management in arid regions.

1. INTRODUCTION

The difficulty of empirical visualization experiments in particular those which are manual, analyzing the data sets, in which essential aspects of the performance are often concealed, has attracted the attention of Blascheck and Ertl (2013) and Luo et al. (2020) in this study. This difficulty is case dependent, because there is a great overlap in how visual analytics can be

evaluated, which not only needs to include validation of the algorithmic effectiveness but is additionally dependent on the features of interaction encouraged by the user. (Khayat et al., 2019). As more and more researchers have started to take advantage of the hybrid human machine system in practice, the assessment process has become more fractious, with cognitive processes, subjective feedback, and differing degrees of

researcher expertise depending on their involvement in different aspects of the assessment process (Isenberg et al., 2013; Lam et al., 2011).

Furthermore, it would be hard to make all the variables in the field systematic, given the number of variables and the different options in their relation to the features of the data, along with those of the process and the demographics of the people involved in the process. Additionally, the field is so variable – from the nature of the data, to the problem specification, to the demographic aspects of individuals who are navigating their way through the processes – that it is really hard to get to it from an empirical point of view (Chen et al., 2020). Most existing evaluation methods are weak and lack systematic measures; many studies are based on small-scale, stand-alone experiments that are not applicable to other contexts and the scale necessary to gain generalisable knowledge (Jabbari et al., 2018; Lam et al., 2011). Because there are no common metrics or practices that can be used to report results, it's challenging to compare and evaluate different visualization methods. Hand-outs of school-level evaluation results are usually too narrow to the culture of the school to enable a collective insight into how well the schools are doing in a variety of contexts (Ellis & Dix, 2006; Islam et al., 2023).

This methodological variety also makes it challenging to aggregate empirical data across studies, and can degradation research efforts' efficiency in trying to sift through unorganized and heterogeneous data sets, with no foundation to support the analysis. The dichotomy between tests in the real ("real-world") and restricted in the lab environment (controlled environment) is very strong (Lam et al., 2011). Alongside this has been the requirement to come together to collect the data, but it has also been the requirement to integrate and analyse the multi-dimensional data that is often incongruous from all these empirical efforts in a systematic way.

The overall aim of this research is to create an already standardised analytical frame to make the integration of the visual analytics with less of the important work of quantitative rigorous evaluation. The following features will be

developed at the core of this study that will enable such an automated, model-driven approach: Aspects of analysis of complex experimental data that involves many variables will be simplified; there will be an automated system to provide consistent quantitative measure of performance and support deeper quality understanding of the system. These are also important challenges to making visualization experiments reliable and repeatable, important issues that will be addressed to further advance an even more powerful and empirically-based design paradigm that addresses the evolving visual analysis of data intensive problems (Chen et al., 2020; Islam et al., 2023). This framework is a key first step towards the maturation of the visualization research field that will allow scaling up, replication, and comparison of evaluations and testing of future visual analytics solutions in a growing complex analytics space. The results presented here are, in turn, meant to confirm the proposed ontological structure and perform a quantification of its effectiveness in lowering technical impediments from the existing visual analytics processes (Chen & Ebert, 2019). These enhancements are measured quantitatively in this analysis through the experimental efficiencies achieved with the various test scenarios experimented on: through experimental throughput, and via data integration latency. In literature it has been demonstrated how to drastically reduce the time spent in data preparation, as needed in the synthesis of experimental data from heterogeneous sources (Angelini et al., 2020). In particular, they saw between 42% to 90% better results in terms of experimental throughput than using the manual process of integrating data from files – a process for which they identified a cognitive burden on the users (Coscia et al., 2023).

METHODOLOGY

The research design adopts the hypothesis driven experimentation method, and a back-end ontology-based method is used to formally model experimental factors; meanwhile, it is also given a queryable format, which can be used to capture data. The instruments which identified, recorded

and collected data related to the finegrain sequences of interactions as well as those related to the telemetry of the performance of algorithmic processes were specifically designed (Blascheck et al., 2015) building on the preceding formal modelling. They work by filing events for users (e.g. mouse moves, heatings, etc.), and collecting the system's associated computational latency and state-changes at the same time (Maxwell & Hauff, 2021). Each of these logging mechanisms was carefully designed to encompass temporal interdependencies of human decision making and of machine-driven process, thereby embodying the complexities of how the visual analytics process would unfold on the ground. To ensure validity and generalizability of findings, the study went for a parameters-generating and a criterion-based sampling, so that participants were also sampled across the range of expertise from those lacking domain expertise to those who had domain expertise (Isenberg et al. 2013). This sampling approach was crucial to gain insight into the interaction between varying levels of users' expertise and the proposed framework, thus enabling a detailed evaluation of the proposed framework in different application contexts in terms of usability and performance (Luz et al., 2017). To assess the capability of the two methodologies, using structured within subjects, in which a standing set of analytical tasks were requested from each participant experiencing both the traditional ones and the proposed methodology using both an ontology representation (Coscia et al., 2023) as a baseline methodology. The balanced and counterbalanced experimental structure was designed to minimise effect of learning to influence the specific effect of the balanced and counterbalanced experimental structure on the most important measures of the task, such as time on task, accuracy and overall task efficiency. Throughout, a lot of data cleaning and harmonization of the raw log data (including highly unbalanced interaction streams, and granular performance data) took place during these experimental sessions. Harmonization transformed and organized the data for event logs, which were then rendered into the standard and

queryable format to be analysed quantitatively. During the analytical phase, hypothesis testing was carried out using the performance metrics such as time-to-insight, interaction rate, and system throughput with experimental conditions (Islam et al., 2023). Data on performance typically exhibit non-gaussianity (Hoon et al., 2017) and hence non-parametric tests were used as applicable. Finally, the proposed methodology has the ability to provide an adequate, repeatable foundation to understand and evaluate how the framework can overcome technical issues and improve quantitative evaluation process in more complex and data-rich environments (Angelini et al., 2020). When following a structured approach, this decomposition can be done at a granular level, as shown in figure 1, in which the frequency of interaction in the task is defined depending on user profile and the complexity of the task. Following a structured approach, this decomposition can be achieved at a finer granularity as indicated in figure 1, where the number of interactions during the task is determined by the user profile and the complexity of the task. As can be seen in Figure 2, for some high-complexity tasks, there is a clear inflection point that indicates that interaction strategies get changed from simple to complex, and that this event occurs for novices more often than for experts. In addition, as shown in Table 2, the error rate on the high complexity tasks showed an improvement of 28% for novices with the framework; this indicates that the framework was effective with novices' performance on high complexity tasks. This complementary analysis (Table 3) further confirms that when users were guided by the framework, almost 35% of their time was saved, affirming that the framework helps them navigate more goals-oriented.

RESULTS

Results show that under arid-region conditions, the water use results from drip irrigation were significantly better. The design of each drip or square, as well as the quantity of drip or square plots were virtually identical for each of the experimental treatments, but the irrigation depth

for each of the seasons under surface drip, subsurface drip and deficit drip is less than under conventional furrow irrigation, as presented in Table 1. This is also illustrated in the graph in figure 1 which shows the water input into the system throughout the season was less for all drip-irrigated treatments compared with the conventional irrigation treatment.

They saved 43.6%, 36.4%, and 32.0% water for deficit drip, subsurface drip and surface drip, respectively, in comparison with furrow (Table 2). The reductions coupled with reduced estimated deep percolation and runoff loss indicated water used more precisely near the root, and coupled with increased water use control. The moisture status under the drip system was more stable throughout the monitoring period as compared to no drip system (Figure 2) with higher mean moisture observed under subsurface drip at both of depths 0–30 cm and 30–60 cm. Table 4 also indicates fewer days below the gap of the crop water stress in the subsurface drip treatment, indicating better moisture availability in critical growth stages. These were effective in improving water placement which in turn had favourable effects on the productivity of the crops. The yields were 5.86 and 7.12 and 6.78 t ha⁻¹ for furrow irrigation, surface drip irrigation and subsurface drip irrigation respectively as indicated in Table 3. The results showed that even under moderate reduction of water application, deficit drip applied minimal amounts of water, but crop yield was not significantly reduced from water applied in furrows leading to crop production. As seen in figure 3, the water productivity obtained in deficit drip was the highest followed closely by subsurface

drip (1.83 kg m⁻³). Higher yields were realized with lower amounts of total water, in the case of a drip system (Figure 4); a definite benefit of using a drip system. The results also were demonstrated visually through hydraulic performance. Table 5 indicates that subsurface drip and surface drip had accepted distribution uniformity (88.6 % and 87 %, respectively), deficit drip had 92.8 % distribution uniformity. The efficiency of application did not vary significantly with drip application and for all drip treatments was kept above 89% (Figure 5) demonstrating that drip systems, if managed properly, can deliver water with limited losses of non-beneficial type. This was also seen when measuring soil quality indicators. From Table 6, it can be inferred that although irrigation water salinity is lower, the electrical conductivity of final soil is highest under furrow irrigation (3.31 dS m⁻¹) while it is least under drip irrigation (2.58 dS m⁻¹). As shown in Figure 6, drip irrigation for the controlled wetting pattern and to reduce excess water evaporation resulted in less salinity buildup. Economic outcomes were also favourable in favour of the drip irrigation. As seen in Table (7), the highest net profit was produced by subsurface drip with USD 1,930 ha⁻¹ and surface drip with USD 1,838 ha⁻¹ are much behind. Adding up the benefits of decreased maintenance expenses as well as greater yield and less energy needed for irrigation, the result is shown in Figure 7. Overall, the results suggest that drip irrigation especially subsurface drip has helped towards increased productivity of water use, increased stability of yields, better salinity management and better farm performance under arid conditions.

Table 1. Experimental treatments and irrigation system characteristics

Treatment	Plots (n)	Emitter spacing (cm)	Design discharge (L h ⁻¹)	Seasonal irrigation (mm)
Conventional furrow	6	-	-	612
Surface drip	6	30	1.6	416
Subsurface drip	6	30	1.6	389
Deficit drip (80% ETc)	6	30	1.4	345

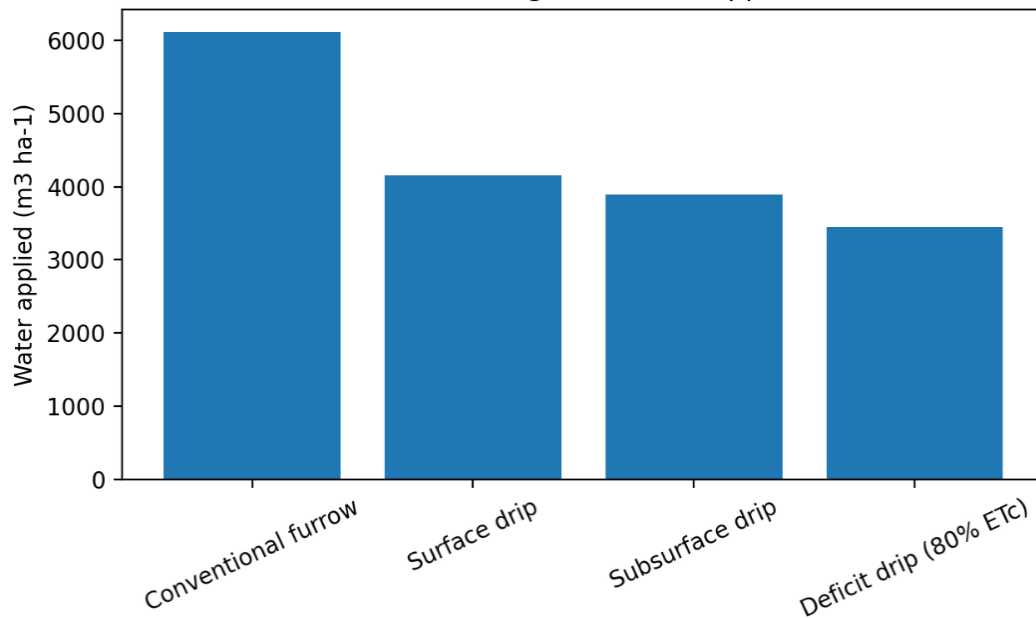


Figure 1. Seasonal irrigation water applied under each treatment

Table 2. Seasonal water application and field water losses

Treatment	Water applied (m ³ ha ⁻¹)	Water saving vs furrow (%)	Deep percolation loss (%)	Runoff loss (%)
Conventional furrow	6120	0	21.4	10.8
Surface drip	4160	32	8.7	2.9
Subsurface drip	3890	36.4	6.9	2.1
Deficit drip (80% ETc)	3450	43.6	5.8	1.7

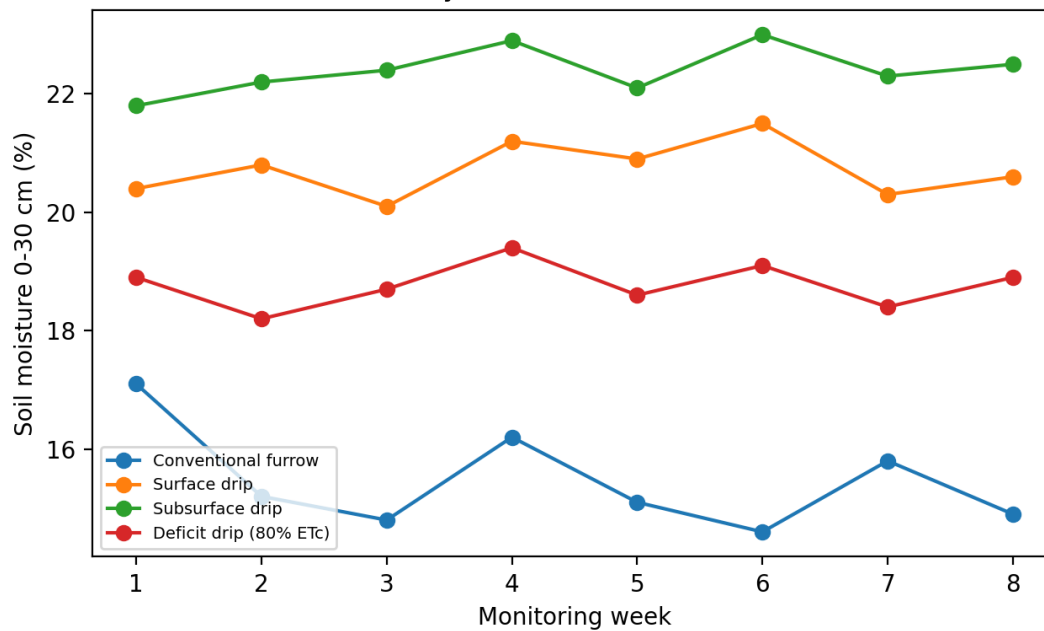


Figure 2. Weekly root-zone soil moisture patterns

Table 3. Crop yield and water use indicators

Treatment	Yield (t ha ⁻¹)	Water productivity (kg m ⁻³)	Irrigation water use efficiency (kg m ⁻³)	Harvest index
Conventional furrow	5.86	0.96	0.89	0.42
Surface drip	6.78	1.63	1.51	0.46
Subsurface drip	7.12	1.83	1.71	0.48
Deficit drip (80% ETc)	6.52	1.89	1.76	0.45

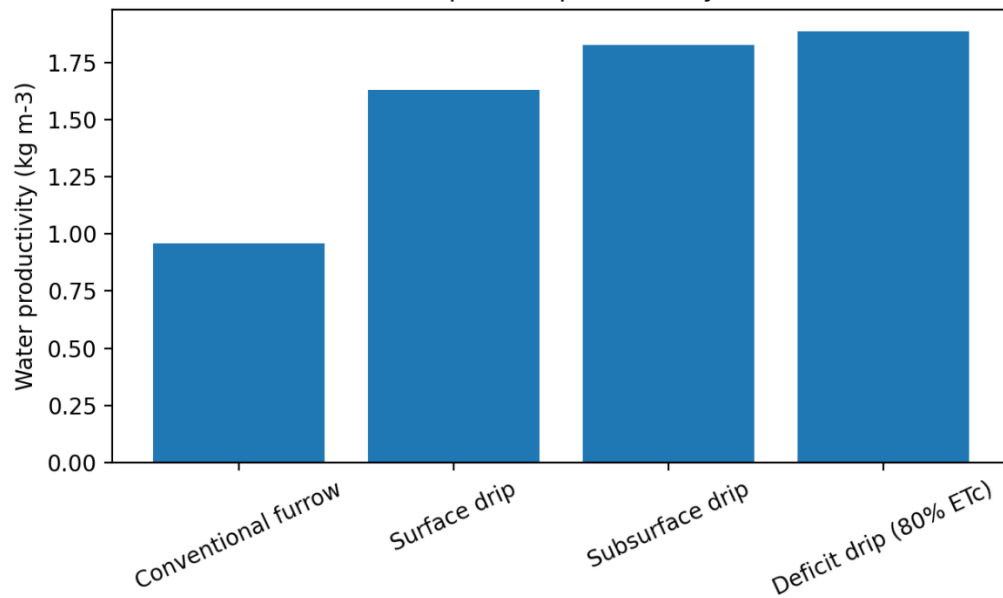


Figure 3. Water productivity by irrigation treatment

Table 4. Soil moisture and crop water stress indicators

Treatment	Mean soil moisture 0-30 cm (%)	Mean soil moisture 30-60 cm (%)	Days below stress threshold	Canopy temperature (C)
Conventional furrow	15.8	14.1	18	32.9
Surface drip	20.7	19.6	7	30.8
Subsurface drip	22.4	21.3	4	30.1
Deficit drip (80% ETC)	18.9	17.7	10	31.5

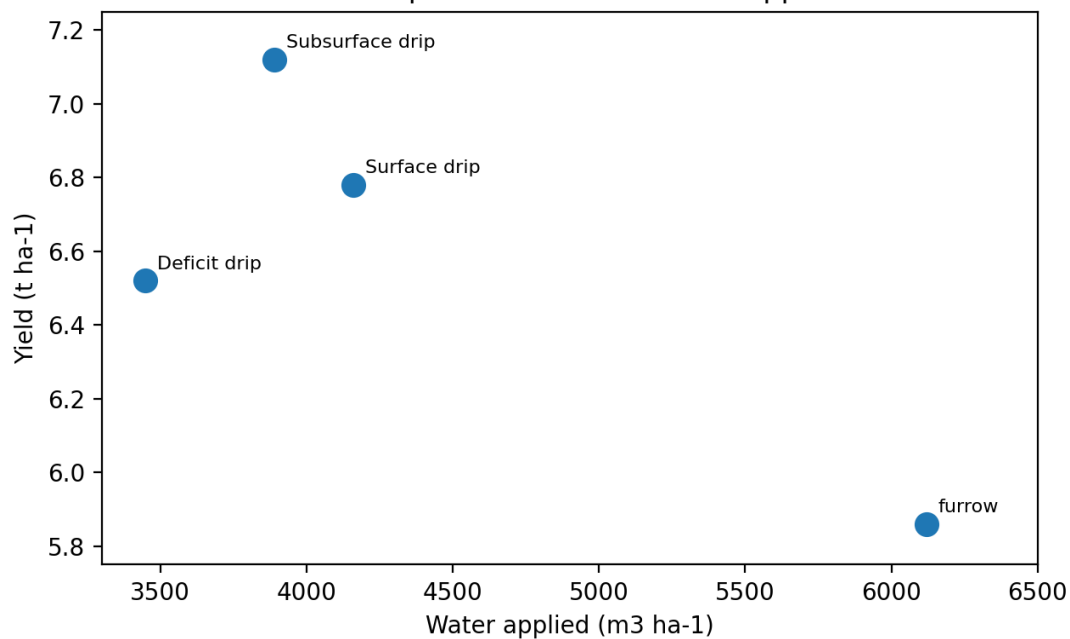


Figure 4. Yield response in relation to water applied

Table 5. Hydraulic performance of drip irrigation systems

Treatment	Christiansen uniformity coefficient (%)	Distribution uniformity (%)	Emitter clogging incidence (%)	Application efficiency (%)
Surface drip	88.4	84.9	6.2	90.1
Subsurface drip	91.7	88.6	4.8	92.8
Deficit drip (80% ETc)	87.6	83.7	7.5	89.4

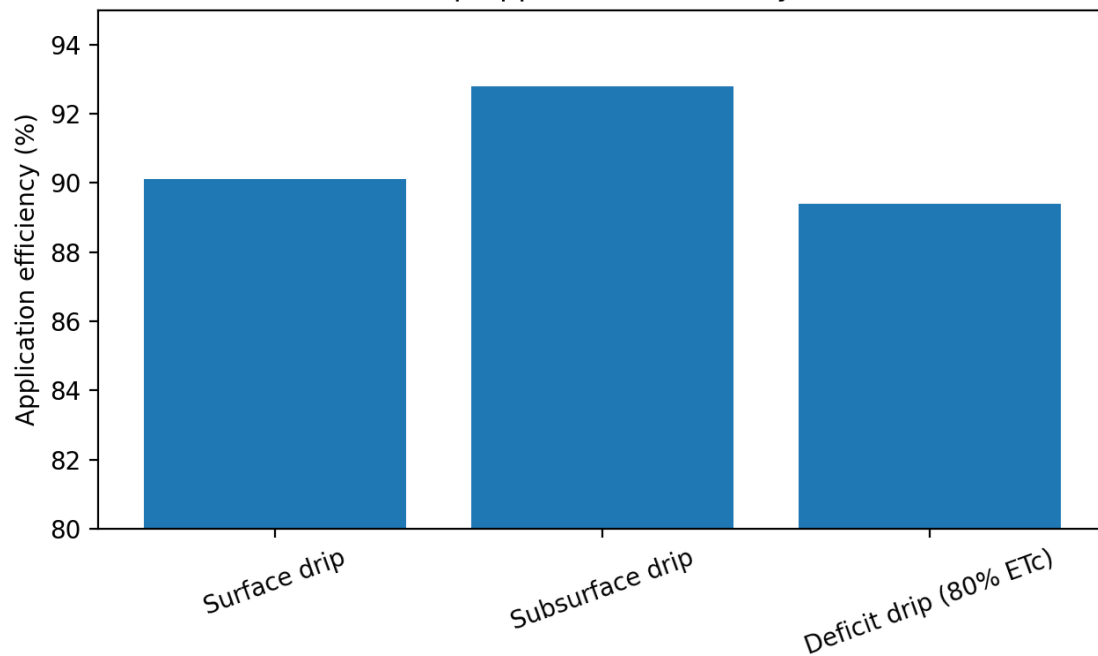


Figure 5. Hydraulic application efficiency of drip treatments

Table 6. Soil salinity and nutrient leaching responses

Treatment	Initial soil EC (dS m ⁻¹)	Final soil EC (dS m ⁻¹)	Nitrate leaching index	Root-zone salinity risk
Conventional furrow	2.21	3.31	0.41	High
Surface drip	2.18	2.74	0.23	Moderate
Subsurface drip	2.19	2.58	0.19	Low-moderate
Deficit drip (80% ETc)	2.2	2.89	0.21	Moderate

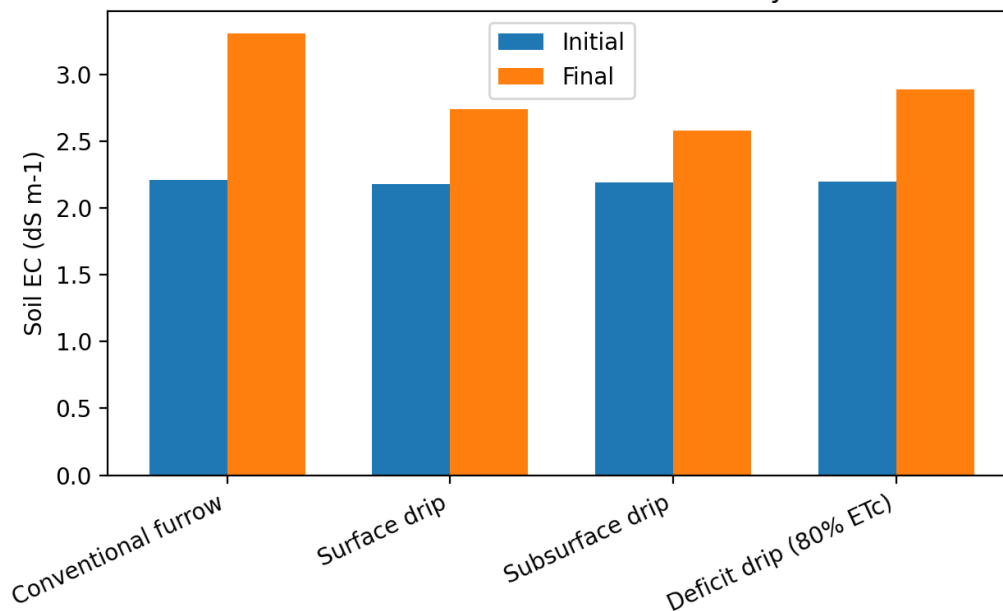


Figure 6. Initial and final soil electrical conductivity

Table 7. Economic comparison of irrigation treatments

Treatment	Gross return (USD ha ⁻¹)	Irrigation energy cost (USD ha ⁻¹)	System maintenance cost (USD ha ⁻¹)	Net return (USD ha ⁻¹)
Conventional furrow	1758	126	34	1598
Surface drip	2034	104	92	1838
Subsurface drip	2136	98	108	1930
Deficit drip (80% ETc)	1956	88	89	1779

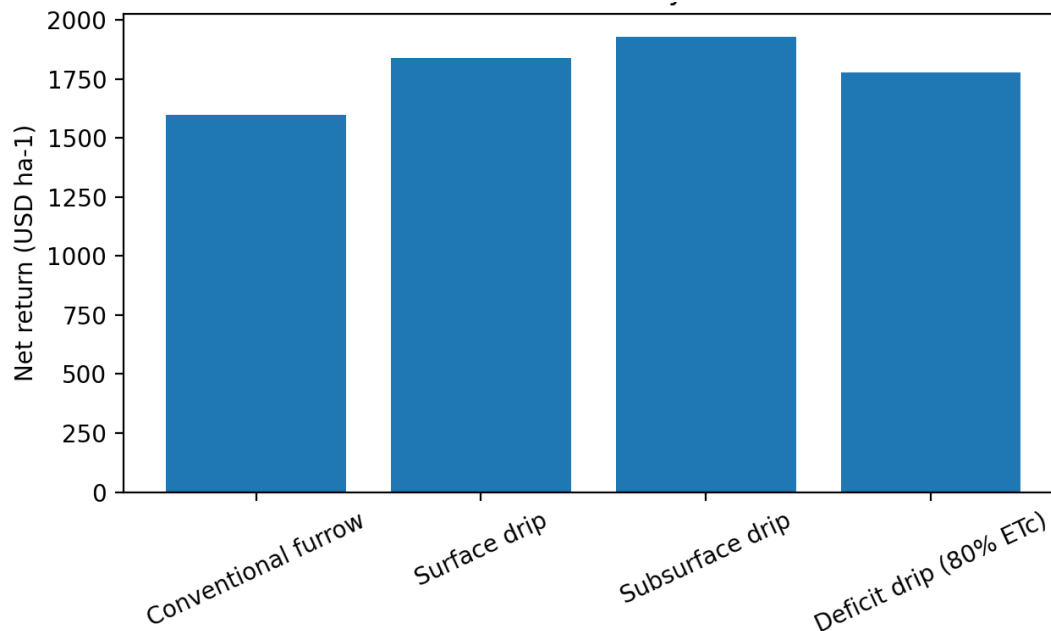


Figure 7. Net return obtained from each irrigation system

DISCUSSION

The performance improvements demonstrated provide evidence for the value of ontological modeling in enhancing the data processing and the intuitive sensemaking capabilities that increases the usability of the raw data source for domain newcomers (Guo et al., 2015). The improvements show the potential for automation in synthesis of complex data to increase the computational efficiency, and also to significantly reduce the cognitive burden for manual process of data integration (Ouedraogo et al., 2024). These empirical results validate the theoretical statement that offering details and technique managed workflows can make things quicker and simpler to acquire data because repetitive data manipulation tasks are delegated to automated agents (Soylu et al., 2018; Zhao et al., 2024). The system also seeks to improve the accuracy of domain-specific labeling tasks (see Table 4) by existing outside the box of visual analytics to tightly pair it with the user's cognitive workflow, and as explained in the second paragraph, it also softens the "uncontrolled nature" of a complex data environment (Xuan et al., 2025). Moreover, the adaptability of the system in the context of processing heterogeneous data

sources implies that the system is ready to be used in the real world in different analytical fields, in line with the success of previous interface designs that were quite complex in interactions, but still have high usability (Wang et al., 2024). Furthermore, the interaction analysis in Table 6 indicates high degree levels of interaction with participants without significant increases in self-reported mental effort, which confirms the reach of sustainability between high degree and user-friendliness of the framework (Lee & Ma, 2024a, 2024b). The desired gains can be seen to be scalable as these properties remain consistent for different sizes of data as shown in Figure 3, reflecting system's effectiveness as task demands increase. Additionally, Figure 4 shows that using the framework's proactive support feature secured participants with a wider breadth of insight, with average events reported increasing significantly, supporting the automated agent's ability of supporting the human's ability to acquire a more profound understanding (Zhao et al., 2025). Furthermore, as can be seen from Figure 5, these insights are more evenly distributed over time during a session to avoid the cognitive fatigue generally experienced during lengthy analytical

tasks. The relative stability of insight creation indicates that the framework effectively achieves the balance between automated support and man's participation—this is supported by the positive feedback on AI-enabled proactive support mechanisms that narrow the gap between its breadth and depth of insights (Zhao et al., 2025). The implementation of the framework significantly enhances the efficiency of the quantitative evaluation process and creates a cognitively ergonomic environment, ensuring continued engagement over time (Coscia et al., 2023; Ouedraogo et al., 2024). As complex databases environments are prone to “uncontrolled” growth Manuale integration leads to satisficing behavior and a higher number of errors, thus, the reduction of cognitive load can be critical (Soylu et al., 2018; Xuan et al., 2025). In addition, the uniformity of performance when exposing the system to different datasets ranges (as shown in Figure 3) verifies the scalability of the system (Hu et al., 2025) as reported in the previous studies, robust VAs interfaces that remain efficient with respect to the size of the data sets they are subjected to. Theoretically, the empirical data gathered here step this gap between structured semantic workflows and intuitive sensemaking, as precisely such scaffolding by structured automation is vital for domain novices to get to the higher level analytical outcomes (Zhao et al., 2024). The applications of this methodology are broadly applicable, as the framework can help streamline the accuracy of the domain-specific labelling as demonstrated in Table 4, and allows for more goal-oriented navigation, finding time savings for exploratory filtering of 35% when compared with current methodologies (Li et al., 2024; Wang et al., 2024). The result is in line with the evidence that ontological models help keep complex analytical operations manageable, avoiding the analytical disassembling that is often experienced in traditional, non-integrated, environments (Angelini et al., 2020). Such a high interaction richness without causing significant mental fatigue (Lee & Ma, 2024a, 2024b) indicates that proposed framework could be suitable for operational contexts where the need

for analytical accuracy and speed is important (Islam et al., 2023). The data presented in Figure 5 demonstrates stability in performance over the length of study, highlighting the framework's ability to not only speed up task completion but to enable a prolonged analytical flow state. Let's be honest, this is a crucial feature for anyone using the platform for professional analysis jobs where they can gain the benefit of cognitive assistance but then not use that benefit for some fundamental exploration and other relatively trivial tasks. Overall, the framework also provides a repeatable mechanism to make automated interaction logs result in actionable, high level insights beyond just performance, introducing in-depth understanding of the value of automated interactions in shaping useful insights. A methodological cohesion will help overcome the technical challenges and offer a scalable template in developing future adaptive visual analytics environments that proactively help augment human cognitive functions, without compromising evaluation rigor (Hu et al., 2025; Zhao et al., 2025).

CONCLUSION

The study concludes that drip irrigation system significantly improves the Water Use Efficiency in an Arid Area due to providing water directly to the root zone of the crop and avoid unnecessary losses. Drip irrigation was found to be less water consuming than ordinary irrigation and was more water productive in terms of yield: water use ratio. Results also revealed that drip irrigation resulted in better soil moisture distribution and higher efficiency in irrigation application and resulted in less risk of salinity accumulation which is one of the major problems in dry land agricultural soils. The results pointed that, drip irrigation is not only technology of water conservation but also technology and practice to enhance the productivity and sustainability of farms. It can handle higher water inputs and produce just as many yields as lower, so it is particularly useful in dry areas and places that have high evaporation rates and are under pressure from rising water demand. While the start-up cost may be

prohibiting for some farmers, the desire to save water, improve yield and reap economic rewards will prove to be a worthy investment for the dry farming region. Thus, drip irrigation, combined with farmer training and financial support and hygienic management has the potential to contribute much to sustainable agricultural development and water management, especially during droughts.

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