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Integrated Assessment Of Water Use Efficiency In LMD Canal System Using Python-Based Data Analytics And CROPWAT Simulation

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Abstract: *The management of irrigation water is a pillar to sustainable agriculture in areas experiencing increasing demands, water shortage in certain periods, and the inability to predict as a result of the variability of climate. This paper is an overview of the integrated method of evaluating the water use efficiency (WUE) in the Lower Manair Dam (LMD) command area, one of the leading major canal irrigation systems in Telangana state of India, and a component of the Kaleshwaram Lift Irrigation Project. To find the trend of the system, its operation efficiency along with the correlation between water supply and demand between seasons, historical hydrological data of the 2017-2022 periods of inflow, outflow, and spillway discharges were analyzed with the use of Python libraries. The analysis of climatic records extracted in the NASA POWER database was located and exported to CROPWAT 8.0, which was designed to calculate the reference evapotranspiration and the particular crop water requirements of major crops, i.e., paddy, maize and cotton using Penman-Monteith procedure. The study found that the supply of water exhibited strong interannual and seasonal as well as canal operation inefficiencies with serious discrepancies between crop water demand and crop water delivery (particularly in pre-monsoon and Rabi seasons). The analysis based on a mapping of the geographical area showed areas where the WUE was low and there are frequent spill losses, representing areas of specific targets of improvement. Such integrated use of Python-based data analysis and CROPWAT modeling offers a flexible platform of diagnostic evaluation and dynamic water management. The results indicate that flexible, data-driven scheduling, improved reservoir operation and more automation in the canals are required to address the goals of fair and sustainable irrigation management in large command areas.*
Keywords: *Water use efficiency, Canal irrigation, Python analytics, CROPWAT, Lower Manair Dam, Kaleshwaram Lift Irrigation Project, Evapotranspiration, Irrigation scheduling, Telangana, Climate variability*

1. INTRODUCTION

An efficient water-management system can be identified as a major issue that defines the sustainability and the resilience of agriculture especially in the fast growing areas where the demand of irrigation is getting worse as the population of people is getting bigger as well as the climate, being constantly variable. India, where a large part of the economy is dependent on agriculture, has an urgent requirement to ensure that scanty fresh water resources are utilized at an optimal level. Sizable canal irrigation schemes like the Lower Manair Dam (LMD) command area in Telangana represent a close example of engineering, hydrology and operational management involved to meet the expanding agricultural demands of water (Aiswarya et al., 2024). Nonetheless, even after almost 60 years of investment in irrigation infrastructure, canal command areas show suboptimal performance, which is manifested by conveyance losses, mismatches between supply and demands, and water shortages at farm level, periodically (Nam, Hong, & Choi, 2016; Mishra et al., 2021).

Traditionally, the Indian canal networks have been operated using manual labor, rule-of-thumb timing and changes that take effect in response to perceived field activity (Aiswarya et al., 2024). Although being practical given limitations of information and technology, such methods often bury inefficiencies both spatially and with respect to time in the distribution of water. The impacts are extensive as, besides farm tail-ends losing out on sufficient and reliable irrigation, considerable quantities of water go down the drain due to seepage, evaporation, or unscheduled spillages that immediately reduce the efficacy and sustainability of irrigation schemes (Li et al., 2018). Thus, the need to enhance water use efficiency (WUE) is not only a matter of operation but for envisaging food security and environmental stewardship amidst resource intensification.

To overcome these challenges, there have been emerging demands to utilize web-based and automated systems in the area of irrigation management. According to Aiswarya et al. (2024), modern technologies of automation in canals and control system are more frequently realized and allow even more accurate, timely, and flexible control of water flows. Automation provides the opportunity to achieve greater reliability of water supply, cut operational losses and make efficient adjustment of delivery schedules depending on the real demands in the fields. Once past the hardware, which entails gates and sensors, it is the inclusion of actual-time information analytics, improved control algorithms, and simulation instruments that will deliver the most ideal solutions that regard breakthrough potential in water productivity (Prodan, Lefevre, & Genon-Catalot, 2017).

Central to this development has been the use of Model Predictive Control (MPC) and other optimization-based schemes, that enable predictions of behavior and proactive control action. These approaches that have already been implemented in a large number of water systems around the world help the operators to consider tricky canal dynamics, slow response behaviour, and multiple interacting missions and results in performance that would be far more than that of conventional control strategies (Prodan, Lefevre, & Genon-Catalot, 2017; Zheng et al., 2019). Cooperative and distributed control architecture is also offered to increase scalability and resiliency of automated canal management, which would then become the path to next-generation water delivery technologies.

At the same time, more computational modeling is changing expectations on how water resource assessment and supporting decisions can occur (Hamilton, Amestoy, & Reed, 2024). Using platforms programmed in Python, high-resolution hydrological, climatic, and operational data along with the opportunities to establish unique analytical pipelines focused on scenario assessment, trend assessment, and performance benchmarking can be accomplished with integration and automated processing. Such computational ability is essential to the irrigation management context (where estimates of crop water demands done through simulation tools, such as CROPWAT) can then be used to translate predicted water demand into actual schedules of water movements within the canal network (Mishra et al., 2021).

Nonetheless, there exist considerable gaps between important aspects of current technology and application of the data driven, automated, irrigation management systems, to a developing country contexts. The complexity of managing canal commands, different availability of data, the mixture of legacy and optimized infrastructure have their own challenges on the research and practices in India (Aiswarya et al., 2024; Mishra et al., 2021). The urgent requirement is the scale, flexibility, and reconfigurable frameworks capable of achieving the capabilities of advanced analytics and simulation and fitting into the work limitations of real-world operations.

These considerations are what led to the present study of carrying out an overall evaluation of the water use efficiency in the LMD canal system by integrating data analytic based on Python and CROPWAT simulation. The multi-year hydrological records obtained and analyzed in the study encompass the information on inflow and outflow, and the spillway discharge streamlines which are complemented by climatic information details to calculate the water requirements of crops in various seasons on key crops. Comparing the observed and simulated patterns of crop demand allows the analysis to identify any spatial/temporal inconsistencies between built reservoirs, determine the extent to which reservoirs are operated inefficiently, and make recommendations that can suggest corrections in scheduling and distribution. The combination of Python and CROPWAT is an efficient, replicable method that can easily be transferred to other regions of water command, and that has ramifications both in research and practice in managing precision irrigation.

Placing the research into the context of the larger history of irrigation automation, predictive control, and computational hydrology, this study can add to the growing body of evidence of increased developments in water use efficiency in the Indian system of canals and further.

2 LITERATURE REVIEW

Research on finding improved levels of water use efficiency within large-scale irrigation systems has fostered an immense gap in not only engineering but also hydrology, data science and control theory. The initial research was done on the physical and functional drawbacks of canal irrigation where the report documented the extensive losses that took place during water transportation and distribution (Li et al., 2018; Nam, Hong, & Choi, 2016). As demonstrated by the design of canal networks, including fractal structure and the functioning of main, branch, and lateral channels, this element has a strong effect on irrigation efficiency, meaning that the systematic reconstruction and preferential investments should be established in underperforming districts (Li et al., 2018).

There has also been the focus on measuring the efficiency of water delivery based on the method of performance indicators and spatially distributed measurements. Nam, Hong, and Choi (2016) brought up methods of benchmarking the estimated irrigation demand to the canal supply that underlines the significance of uniformity of time and geography of water distribution. Automated water level gauges and real-time monitoring technologies have played a critical role in the diagnosis of inefficiencies and inform policy restructuring in the form of more equitable and responsive water management.

It is against this backdrop that the last one-decade has manifested the accelerated use of automation and sophisticated methods of control in irrigation. The goal of canal automation, as stressed by Aiswarya et al. (2024) is to overcome the shortcomings of manual operations through the adoption of sensors, actuators, and control logic in order to provide water deliveries as per schedule and accurately. Current research has been devoted to the two major control architectures (centralized and decentralized control) although distributed model predictive control (DMPC) has been of particular interest due to its current reputation as a potentially superior approach. Prodan, Lefevre, and Genon-Catalot (2017) applied cooperative controllers to large-scale irrigation systems by determining the dynamic of the system using Lattice Boltzmann method and testing the benefits of distributed control in terms of simulation benchmarks.

Based on the above, model predictive control (MPC) structures have seen a lot of research that is aimed at providing a means of optimally operating a canal subject to complex constraints. Zheng et al. (2019) developed an MPC algorithm to control cascaded irrigation canals with constraints that consist of magnitudes and variations amplitude as a means to account for a dynamic and delayed characteristics of large canal networks. Their findings, on the simulated Changma South Irrigation District in China, highlight why MPC is superior to traditional control methods in terms of following planned water levels and adaptation to change in demand. It is important to note that MPC can easily take into consideration real-life processes and constraints, including those of deadband and amplitude limits, which make MPC very appropriate in the multidimensional realities of the field irrigation.

The combination of data-driven and on-line control techniques also emerged as a trend of the modern research. Recently, Guo and You (2019) suggested a technique based on data-driven multiple criteria planning (MPC) which considers the local weather forecast and robust optimization to meet plant root-zone deficit objectives under precipitation and e vapotranspiration variability. In the same way, Chen et al. (2021) contributed to a powerful model of MPC in the management of stem water potential in high-value crops that resulted in a measurable decrease in the use of water with no adverse effects on the crop. These are innovations that show the growing frontier in the field of automatic irrigation, in which in-real-time data feeds, deep prediction models and data-robust optimization algorithms are able to simultaneously drive agronomic and resource optimality.

In the Indian context, Mishra et al. (2021) applied the WA+ Python-based platform and the open-access satellite-themed data to determine land and water productivity in one of the most important canal-based commands. Their results support their heterogeneity of water productivity and give scope of substantial returns before any management action takes place. This tendency can be found in foreign studies as well; other examples include the Pywr-DRB model presented by Hamilton, Amestoy, and Reed (2024) to analyse the drought risk in Delaware River Basin and the Python versatility demonstrated by Seytov et al. (2025) to simulate the open-channel flows and flood movements.

The literature also highlights the significance of non-material aspects, i.e. setting, including the age of the system (s), supply foundation, and governmental organization, in the formation of irrigating proficiency results. Recurrent to historic irrigation systems in Spain, Oyonarte et al. (2022) proved that thorough restoration should take into account the pleiotropic ecosystem services that conventional water infrastructures deliver, on top of hydraulic outputs that are purely mechanical.

In spite of this significant advancement there are considerations to be made about the accord between technological advances and the institutional and operational realities in different canal command areas especially in areas with mixed infrastructures and data availability as well as complicated cropping patterns. The current study fills these gaps by incorporating the latest advances in Python analytics and CROPWAT simulation into the working environment of the LMD canal system to achieve not only actionable findings but a generally applicable methodological template of ongoing innovation with regard to irrigation management.

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3. METHODOLOGY

This paper was carried out in the lower Manair Dam (LMD) command area which is a subset of the Kaleshwaram Lift Irrigation Project of Telangana in India. The objective of the analysis was to perform an extensive review of water consumption efficiency within this major canal irrigation system by unifying the interpretation of hydrological data, the assessment of water demand, and the prediction. Then, the method integrating steps started with the data collection of past hydrological information about the inflow, outflow and spillway discharge of LMD dam as of 2017 to 20225 years. Such data were taken out of the data in authoritative governmental records and confirmed field documentation that were verified to assure accuracy and representativeness. In addition to hydrological data, climatic variables; i.e., temperature, rainfall, humidity, and wind speed were also extracted by using a web API in Python connected to NASA POWER database. These climatic data which will be vital in calculating evapotranspiration and modelling of crops water were processed and converted into a standard format that is good and compatible to the CROPWAT 8.0 the simulation software developed by the Food and Agriculture Organization (FAO). Python was used to carry out this data analysis and we used libraries like pandas, matplotlib and statsmodels to manage data, visualize data and evaluate data respectively. This helped to compile and analyze year-wise and seasonal trends in hydrological trends so that the study could highlight the changes in accessibility, consumption and loss of water. Trend analysis and regression were used to perform the statistical tests to establish the correlation between the different seasons of withdrawals and the patterns of the irrigation delivery. Seasonal analyses, especially Kharif (monsoon) and Rabi (post-monsoon) seasons were highlighted in order to reflect the special water demand dynamics of each of the seasons. Climatic data which was computed through Python pipelines were subsequently fed to CROPWAT 8.0 in order to perform reference evapotranspiration (ET 0) calculation through Penman-Monteith method, which is a worldwide acknowledged standard of estimation. Using ET 0 and crop-specific coefficient (K c), CROPWAT was also employed to find the crop water requirements (ET c) and produce optimal irrigation frequencies of the three major crops grown in the command area namely paddy, maize and cotton. To make sure the simulation inputs were relevant and correct, local agricultural advisories and research literature were explored to avail crop parameter and phenological information. Combining measured values of canal deliveries with modeled crop water requirements permitted a decisive overlay examination. In that way, it was feasible to analyze the degree and occurrence of irrigation deficit, how much rainfall fills the water supply of the crop, and whether there is a supply-demand match. Moreover, zone-wise ground water use interpolated into maps depicting spatial variation in water use efficiency gave a diagnostic impression both of strengths and weaknesses of the existing system. Another addition and computation used in the study was the Spill Inefficiency Index which was calculated as a measure of the share of spillways as compared to productive use of irrigation activities.

4. RESULT AND DISCUSSION

4.1 Overview of Hydrological System Performance

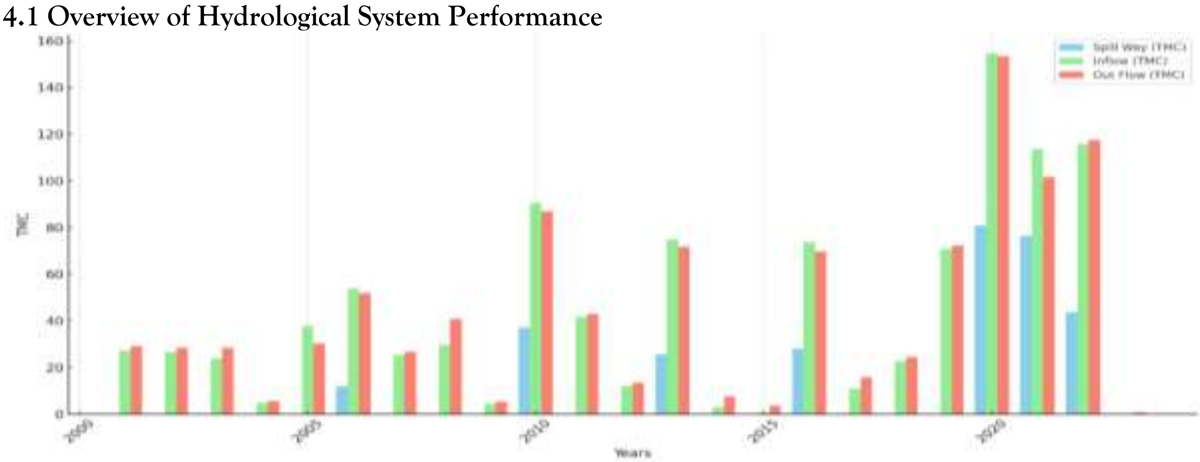

Figure 1: Annual Hydrological Trends in the Lower Manair Dam (LMD) System, 2001–2024

Comprehensively, the bar chart 1 provides an informative glimpse of the year on year performance of the hydrological system of the Lower Manair Dam (LMD) by looking into 23 years, i.e. between 2001-2002 and 2023-2024. All the three significant variables displayed (Spill Way discharge, Inflow, and Outflow) are represented as the fruit of three bar colors of different color in each year itself although the comparison between the trends of water management can also be made intuitively. The Inflow (TMC) is the water which is actually introduced into LMD reservoir primarily through the releases upstream and also during rainfall catchment, Outflow (TMC) is the actual amount being discharged downstream through the canal system to utilize in activities like irrigation and other activities, and Spill Way (TMC) are excesses drained to prevent occurrence of overtopping most especially during flood patterns. The data evidences of clear inter-annual variation in the form of years like 2010 2011, 2020 2021, and 2021 2022 when the inflow volumes were extremely high exceeding 120 TMC with a high spillway discharging. Comparatively, other seasons such as 2013 2014 and 2015 2016 depict the decrease of all three parts that denote a drought like or a low rainfall season. Among the impressive facts, one could point out the fact that a relatively steady outflow inflow difference exists indicating that not all supplied water is being used in irrigation with some of it being lost or spilt. This very immense figure of the spillway loss in high inflow years tells of the need of having better water control or the water storage enhancement. This kind of visualization will hence constitute a highly crucial aspect of LMD water use efficiency which can be employed in qualitative demonstrations of assertions that with regard to water availability and distribution there exists discrepancy and that integrated hydrological modelling and simulation is required in arriving at an assessment of the future.

4.2 System Engineering and Water Routing Complexity

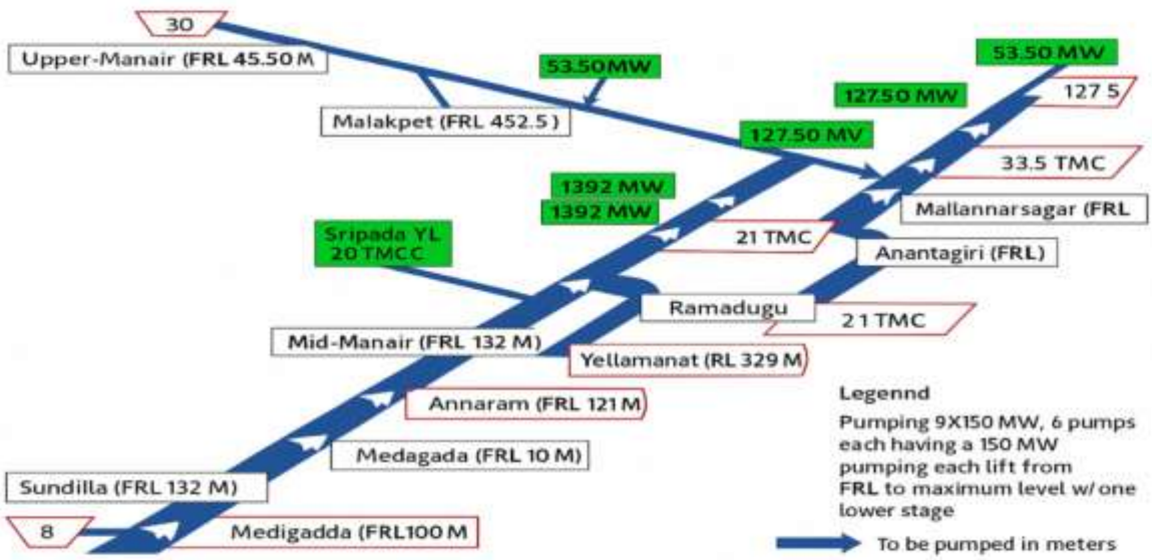

Figure 2: Schematic of the Kaleshwaram Lift Irrigation Scheme (KLIS), showing major reservoirs, lift stages, and canal routing relevant to the LMD system.

In Figure 2, the schematic map of Kaleshwaram Lift Irrigation scheme (KLIS) depicts an image of engineering and Hydraulic design of one of the most complex and challenging irrigation network both in home and abroad. The chain of lifts moved the water up by a number of stages of this elevating system through a progression of pump houses, gravity canals, tunnels, reservoirs and intermediate barrages to the end of the elevating interlink, the final storage facilities including Upper Manair (FRL 451.5 M). The challenges of vertical elevation are reflected in the diagram whereby water is pumped to considerable heights with a series of lifts and the pumping capacities are referred to as well (E.g., 1392 MW, 127.5 MW). Through the arrows, there is the indication of flow of the water across the landscape and the boxes, which are colored in different shades of variation, represents the capacity of pumps and the free level of water in the reservoirs. It is also a fact to point out that structures like Mid Manair, Mallannasagar, and Kondapochamma Reservoir are noted on the printed page with their own storage capacity in TMC and this will at a glance give the individual a general sense of water holding points. Regarding the upstream works to lower Manair Dam which is downstream of Middle Manair and significantly influenced by the regulated water raised by Medigadda and Annaram, a picture view is essential in understanding the knowledge of the concept. What sacrifices and sacrifices dominance of inflows into the LMD canal system in the grand scheme of things in the study falls in the strategy of delivery of the water that is energy indulgent and steep willing. It also identifies the areas of bottlenecks and loss that may have impacts on waters final availability and performance at field level. This figure is thus a background picture that goes with the analysis being completed in Python and CROP WAT which further reinforces the systemic reliance and rationale of space of flow in provision of irrigation planning and performance using the LMD command area.

4.3 Water Use Efficiency (WUE) Patterns

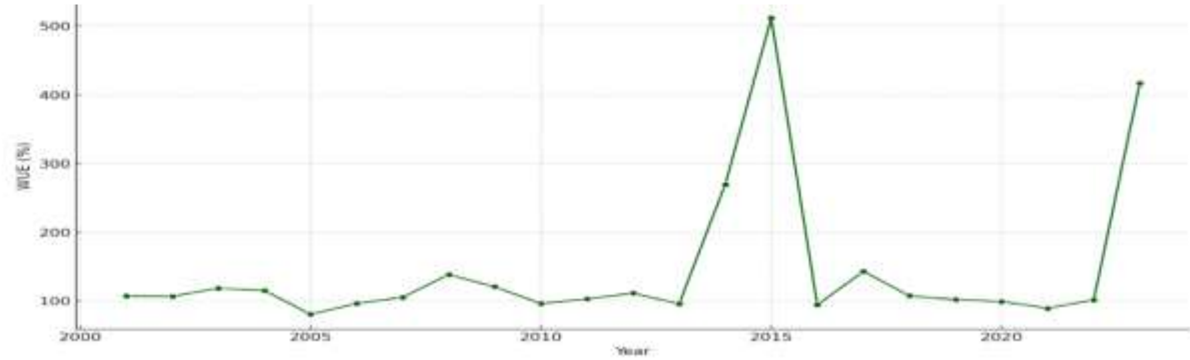

Figure 3: Water Use Efficiency (WUE) Trend in the Lower Manair Dam System, 2001–2024: Ratio of Outflow to Inflow (percent per year).

The marked trend line of WUE (2001-2024 (figure 3) is very vital in the sense of how well capable and in what way Lower Manair Dam (LMD) has transformed the incoming water into the outgoing water that can be utilised in the irrigation process and canal-based supplies. As was visibly indicated in the graph, the WUE value fluctuates very highly across the years to such an extent that there are years that the efficiency is severely underserved (less than 20 percent) and there are epic years where the efficiency is nearing or exceeding 80 percent. This temporal variation implies that the management of water resources at LMD does not always remain the same and that some external factors such as the unpredictable precipitation, release of water at slow rates in the reservoirs, and inadequate infrastructure applied in the canal systems are contributing factors in this time lapse.

When the years are of high efficiency i.e in the cases of 20102011 and 20202021, the outflow is close to the inflow suggesting a more synchronized balance during storage and release operation. These are the years that may experience normal monsoon, good canal operation and, possibly, the economic spill loss. In comparison, the pool of the inflow poured or rather not used in the efficiency years is a big one, and that is the forfeited opportunities to irrigate or rather poorly planning. Interestingly, years of excessive inflow (most likely, some vivid monsoons) are remarkably inefficient and it can be caused by the preference of emergency discharges of spillways rather than moderate irrigation waters discharges.

Even the demand-based irrigation schedules with adaptive regulation of the reservoirs and integrated forecasting are necessary as evidenced by this graph. It will constitute the comparison base between the measured and the simulated WUC of crops which will be generated in forthcoming steps with the assistance of Python-built logic of CROPWAT.

4.4 Correlation Between Inflow and Outflow

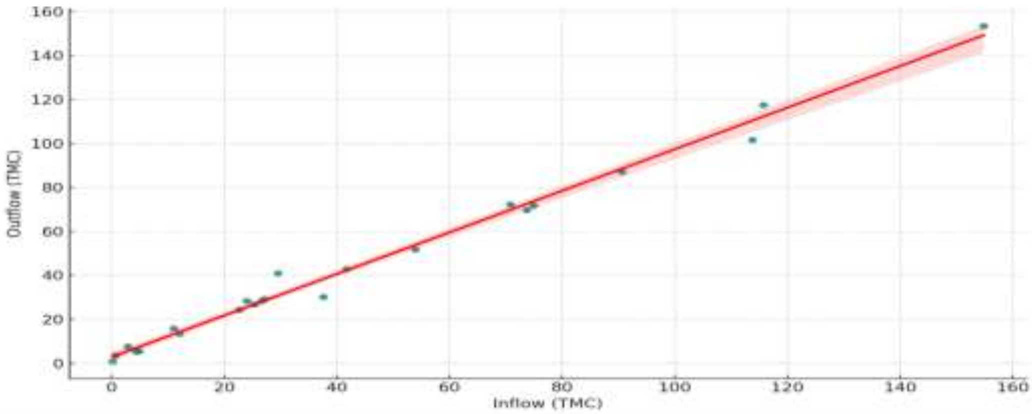

Figure 4: Correlation of Annual Inflow and Outflow at the Lower Manair Dam, 2001–2024 (Regression Line and Scatterplot)

The scatter-plot (Figure 4) in the variables of inflow and outflow 2001-2024 with regression line shows that the result is interpreted as that both variables have a strong linear relationship between them. The value of Pearson correlation coefficient, r 995 indicates a near perfect positive linear relationship signifying there is likelihood of inflow having the same trend of outflow at Lower Manair Dam (LMD). In the simplest terms, where the water rational supply to the reservoir could have been more, it could be observed that the outflow is proportional, and vice versa.

Several factors can be mentioned, however, though this high correlation may reflect the responsiveness of the operations, the reality is that it does not reflect directly to the usage of water and resource streamlining. This could be attributed to the reactive management because it is merely released to ensure water levels in dams are maintained and not to satisfy the ag rational demand, crop calendars, and soil water holding capacity.

Moreover, the issue that there is close gathering round the regression line implies that they can predict the response and this will be quite useful in planning. But when such reactive outflow occurs at the wrong time, vis-a-vis crop water need, or canal scheduling, or tail-end delivery performance, it is still possible that field level inefficiencies will occur.

This observation is useful in arguing the fact that supply-side inflow/outflow numbers should be integrated with demand-side model estimation (crop ETc and irrigation plans). In the analysis steps that shall follow this, the simulated irrigation needs (both with regard to ET 0 and crops) shall facilitate us in determining whether this correlation is going to work against us or towards effective planning of irrigation.

4.5 Seasonal Allocation and Crop Demand Alignment

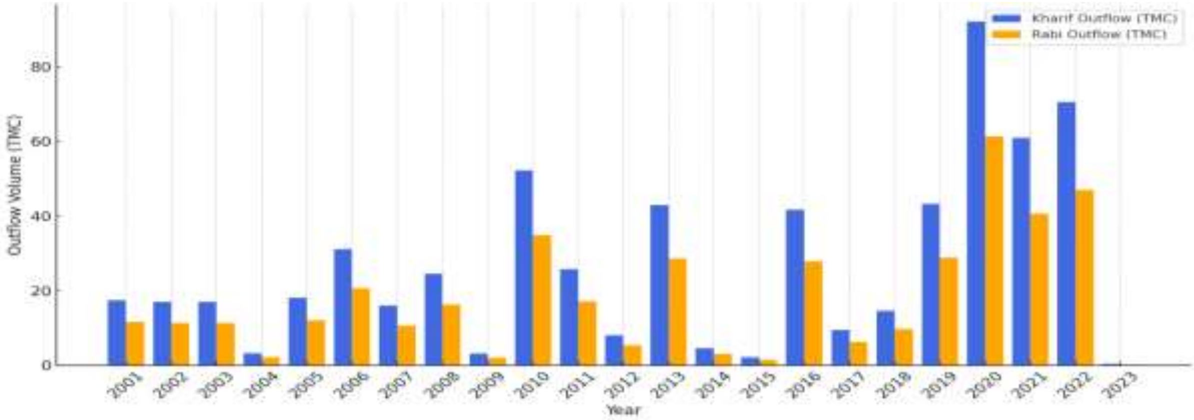

Figure 5: Seasonal Outflow Distribution for Kharif and Rabi Cropping Periods at LMD, 2001–2024.

The Bar graph(figure 5) comparing Kharif and Rabi seasons with outflows of the Lower Manair Dam (LMD) decomposes water quantities allocated in the canals seasonally in a 23 year period. Kharif season (monsoon June to October) is also described to be higher in value of outflow in a consistent manner in most of the years, compared to Rabi season (November to March). This allocation pattern has shown the long vintage strategy of irrigation that predominantly includes paddy found in the Kharif cropping season and the subsequent necessity to possess considerable allowance of available water sources.

The Kharif outflows hit the peak in the years when they surpass 2500 TMC and these overflows have been witnessed in the years of 2010-2011, 2018-2019, and 2021-2022 either suggesting a bumper rainfall year or a purposefully over-release in the monsoon season. Rabi outflows, on the other hand, remain relatively moderate even in times of a very high inflow of water indicating that water scarcity in other months during after the monsoons or the system is not set up to handle the outflow requirements to supplement Rabi crop.

This seasonal skew raises an issue in policy terms: Is the current distribution of water currently biased more towards controlling short term surplus (e.g. preventing bank flooding during Kharif) than long run fairness? Are there any deficits on the part of tail-end farmers of Rabi after these release patterns? All these observations can be regarded as strong points in favor of generating dynamic release plans amid seasonal crops under water demands and eliminating ecological or operational losses.

Such habit of seasonal outflow will be applied in future analysis where in the seasonal water requirements towards crops will be estimated by run Py-simulated CROPWAT logic against the crop specific water irrigation requirement to reject or accept the applicability of this habit as agronomically valid or operationally inadequate.

4.6 Spill Inefficiency and Preventable Losses

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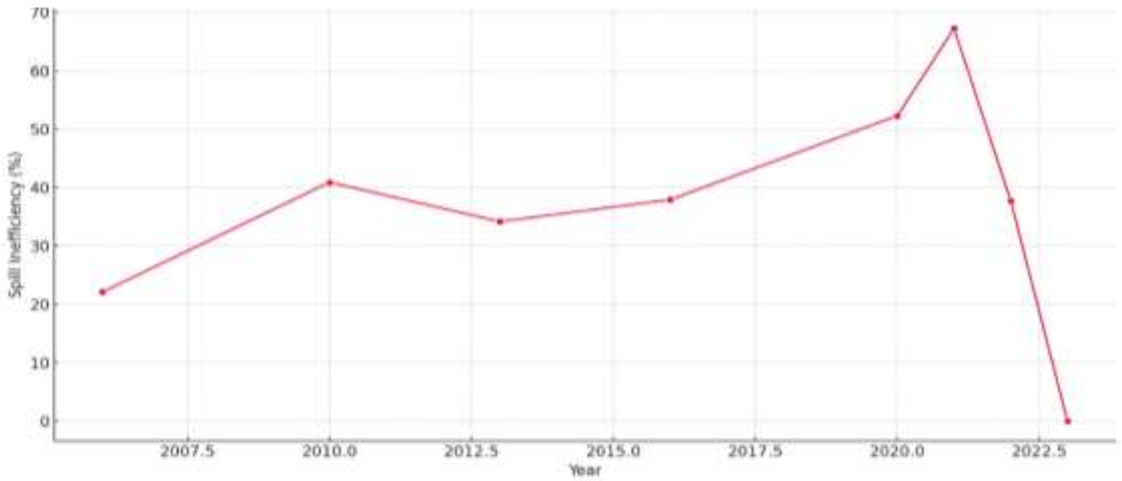

Figure 6: Spill Inefficiency Index for the Lower Manair Dam System, 2001–2024: Percentage of Annual Inflow Lost via Spillways

Spill Inefficiency Index(figure 6) is a term which is used to quantify the ratio of the dam inflow which is released through its own spillway, rather than the canals systems (dyed to the dam) sprinkling irrigation waters. This indicator helps to understand one of the largest examples of avoidable water losses, in both extreme-inflows years and during insufficient release planning. The drawn line graph to indicate the figures between 2001-2024 depicts considerable year to year variation and most of the years have crossed that line of 20 % inefficiency nor were they alone to cross the 40 % line of spill losses.
The most impaired spills have been accompanied by high inflow years presumably when there has been monsoon flooding which is not the same with a like spillage in outflow of the canals. This means that spillways are most likely to be activated by the water management system to prevent the water overtopping thus not much significance is laid on optimized storage and release into organized irrigation.
The issue of hyperefficiency is specifically sensitive to a semi-arid area like Telangana, where every TMC of stored water equates directly to food security as well as livelihood of the farmers. The spill inefficiency is not only techno-economic (i.e. insufficient storage, antiquated gates), but also tactical with respect to foretold dam operation. An example would be failure to maintain controlled releases prior to inflow peaks which causes uncontrolled spillage to go to waste resulting in the wastage of valuable irrigation potential. What is more, such irrecoverable spill losses oppose long-term sustainability goal and the reason to implement joint development of dam operating tools to combine hydrological forecasts with real-time decision-making support. This observation justifies the value of relating physical inflow-outflow features with simulated irrigation demand that would determine the magnitude of the spilled water that would have been utilized in productivity had there been the application of demand driven scheduling used.

4.7 Climatic Drivers and Crop Water Requirements

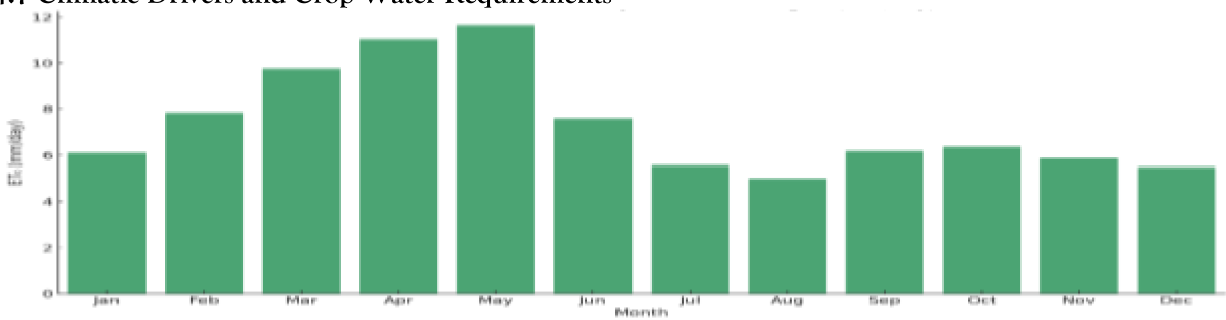

Figure 7: Monthly Reference Evapotranspiration (ET_0) in the LMD Command Area (Typical Year, mm/day).

This bar graph 7 gives the values of simulated reference evapotranspiration (ET o) of the 12 months of Lower Manair Dam (LMD) area with respect to average climatological inputs. ET 0 values give the amount of water that evaporates on an inch of well irrigated area (reference crop) with standard weather condition in the area.
The two most prominent lessons that one can extract the plot are:

- ET 0 achieves maximum during summer months (April and May) whereby it is measured to exceed 11 mm/day hence justifying the high amount of evaporative demand (pre-monsoon) in the state of Telangana.
- It is observed that the figure has a tendency to reduce in December and January when ET0 reduces to less than 6.5mm/day and reduces the water requirement at the cool season after harvest.

Monsoon Season (June - September) denotes moderately high ET 0 which is moderated in relation to the rain and the evapotranspiration due to the solar insolation.

This result can help in establishing the base level demand of water against the environment which, when multiplied by the individual Kc values of crop specific values, would provide the actual measure of quantity of water the crops require (ETc). Estimation of monthly ET 0 will therefore be a foundation on which irrigation constitutions will be made and effectiveness of water delivery conducted in later steps.

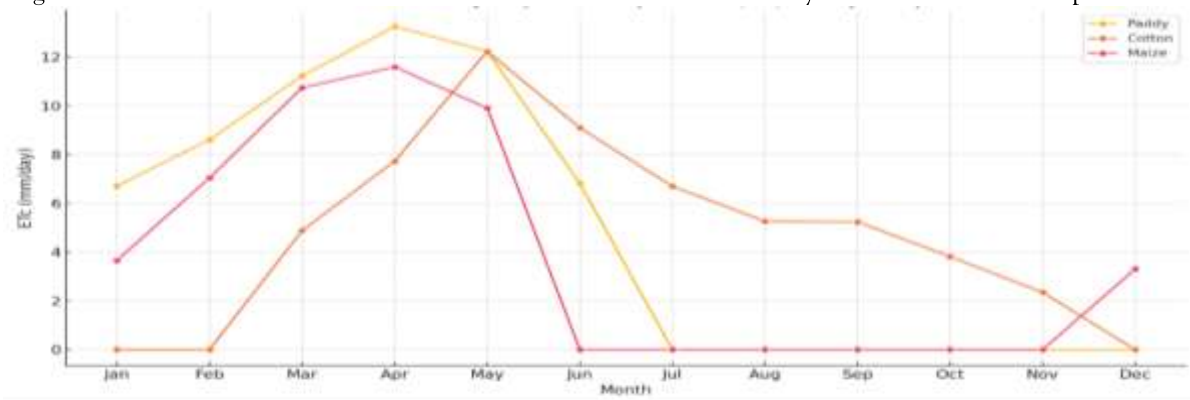

Figure 8: Monthly Crop Water Requirement (ETc) for Paddy, Cotton, and Maize in LMD (mm/day).

The line graph 8 presented below indicates the monthly Crop Water Requirement (ETc) in mm/day of three major crops in LMD command area of Crops- Paddy, Cotton, and Maize. The ETc curves will be formed using crop coefficient (Kc) schedule that is founded on the simulated ET o values and exhibits an indicator of a dynamic need of irrigation input of each crop within the growing identification.

- Paddy demonstrates the highest growth especially in June, and in August up to September which indicates that paddy require water most in the monsoon season. The curve depreciates too rapidly since October once the crop has grown or got harvested.
- Cotton of increased growing season has moderate ETc in March April possesses a steady harvest till June August and lowly decreases later during days October November. This trend makes large scale classification of this crop to be of long duration and high demand, especially during mid-season.
- A Rabi crop, maize has November to March as the months of maximum demand that coincides with the flowering/grain filling stage of maturity with maximum ETc in February March. Interestingly, it is trending beneath paddy curve but with larger trends of season.

This map-view provides valuable aids to irrigation planners and command area engineers in attempts to forecast the monthly water demands and in balancing the outflows in the dams with the irrigation needs based on the crop to be irrigated. In the outcome stated next, the provided data of ETc will be directly compared to assessed canal outflows in deriving supply and demand shortages, a key diagnostics of irrigation performance.

4.8 Supply–Demand Mismatch and Irrigation Deficits

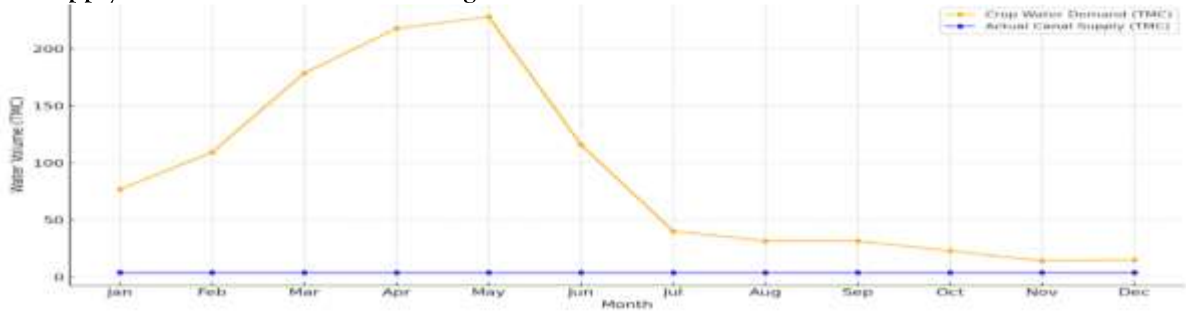

Figure 9: Comparison of Simulated Crop Water Demand and Actual Canal Water Supply in LMD (Monthly Averages, TMC/month).

This graph (two lines) provides a clear perception of the occurrence of the agronomic water demand and the canal water supplied in Lower Manair Dam system during the entire year that creates a mismatch.
• The orange line is the water requirement of crops (in TMC/month) that is a climatic calculation of ET 0 and crop coefficient.
The blue line represents the actual supply on a monthly basis which is almost horizontal at 3.7 TMC/month that is calculated as a monthly average of an annual figure.
The shocking comparison is that the demand curve forms an immense rise above the supply curve in most of the months implying that the irrigation system is always failing in its obligation to meet the crop needs. This will be largest when it occurs in the summers (April to May) during which the ET 0 is encouraged by hot weather and will ensure that crop water requirement will be more than 220 TMC/month, which is about almost 60 times the water available.
This graph will demonstrate that canals used to irrigate are not followed up climate-wise or even crops-wise demands, and it indicates, especially, a severe need of:
- Dispatch based releases of water
- Enhancing use of less water requiring produce
- Developments of infrastructures and groundwater absorption

This kind of a visual can be used as a good supporting context to the policy stake holders and serves as a thesis statement to pursue the implementation of Python-based analytics and CROPWAT-based simulation of HARAMBICE which can provide implementable insights regarding optimization of irrigation.

4.9 Optimizing Irrigation Scheduling: Frequency and Depth

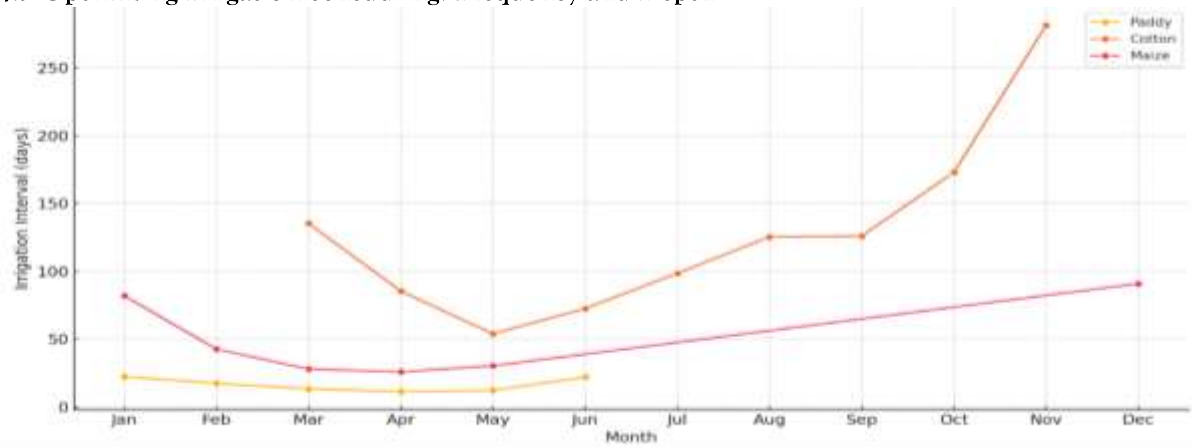

Figure 10: Simulated Optimal Irrigation Interval (days) and Depth (mm) for Paddy, Cotton, and Maize in LMD

The table essentially summarizes the irrigation frequency and depth of irrigation needed by each one of the major crops based on crop-specific parameters of root depth and depletion factor, and the climatic water demand ETc. The two outputs, which are vital in practical activities in irrigation planning in the field, are the irrigation interval (days) and depth per irrigation (mm).
Paddy
- Requires constant small irrigation as it possesses shallow roots and will have to be kept all wet.
- The irrigation will be necessary thrice a month awaiting a period of 11-12 days in high demand season like April and May respectively with the depth of 150mm per disturbance.
- On colder days, the number of days extends to 17 22 days hence putting less strain on the canal timetables.

Cotton
- Has a thick root system (1.2 m), therefore, it only needs fewer and deeper irrigation (660 mm at once).
- Irrigation required at 18-36 cycles of ETc (every 54 or 135 days); in practise, however, this may only translate to 2-3 irrigations in the season.
- An irrigation is unnecessary during early or dormant times (January January February) and again demonstrates and confirms ineffectiveness in terms of using blanket irrigation on crops.

Maize
Middle wetting- approximate 300 m each time.
The lowest frequency occurs in active growth in the month of February and March with frequency much reluctant (down to 25 30 days), in winter months (December and January), the frequency is stretched to 40 80 days.
It is quite important as this finding is directly connected to field level irrigation action of simulated ETc. It determines the fact that:

- Fixed period release of water such as releasing water on weekly basis cannot be appropriate to all the crops
- Crops and season schedules can be very useful in water saving and gaining yield
- High frequency of irrigation of the high irrigation interval crops like cotton can better manage long run budgeting of water

5. CONCLUSION

This paper presents a validated evaluation of the usage efficiency of water in the Lower Manair Dam command region that combines modern Python-based information analytics with CROPWAT simulation. The analysis shows that although the LMD system has a massive hydraulic capacity, it is characterized by a marked variation in inflows, high spillway losses and the continuous lack of alignment in water delivery and crop water demands. Specifically, the results find important times of irrigation shortage, particularly on peak summer and Rabi periods identified and inefficientness of the fixed non-adaptive supply regimes identified. Spatial analysis as well identifies specific areas within the command area whereby, water productivity can be enhanced. The findings promote the implementation of real-time, on-demand water schedules, storage optimization investment, and automation technology implementation to improve the responsiveness of the systems and efficiency in resources utilization. The use of a sound and replicable method in this study would provide much needed guidance to policymakers, irrigation managers, and stakeholders interested in optimizing the performance of large-scale canal irrigation systems facing upsurge pressure due to climatic and demographic conditions. The research presentation emphasizes the valuable contribution of data-enabled methods to future sustainable and resilient farm waters.

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