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Using data mining techniques to identify the impact of water availability in the agricultural sector

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Abstract. This paper comprehensively analyzes the impact of water availability on the agricultural sector, focusing on several key aspects. The study evaluated soil composition and its relationship to crop yields and productivity, as well as the efficiency of different irrigation methods. Special attention was paid to seasonal changes in crop production and their dependence on water resources. The analysis also covered economic indicators, including crop prices and water costs. The used methods of data mining allowed to study in depth the impact of water availability on the agricultural sphere. Correlation analysis revealed that water availability has a significant impact on crop yields and productivity, but this impact is not decisive. In some cases, other factors such as soil composition and agronomic management practices applied played a more important role. Factor analysis identified key factors affecting crop yield, including not only water availability but also soil type, climatic conditions and agronomic practices. It was found that although water availability has an impact on production, it is by no means always the main determinant. The clustering of data showed that there are groups of factors and conditions that together have a complex influence on the results of agricultural production. This confirms that optimization of agricultural activity requires consideration of many variables, not only water resources availability

1 Introduction

Agriculture, as the foundation of food security and sustainable development, encompasses many aspects and practices necessary for efficient and productive production. The main areas include not only crop and animal production, but also the production of various food products and raw materials such as textile fibers and biofuels. These processes require an integrated approach incorporating modern technologies, innovative management techniques and sustainable practices.

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Soil quality plays a central role in agriculture as it directly affects crop yields and plant health. To achieve optimal results, it is important to consider not only the physical and chemical properties of the soil, such as nutrient content, pH and structure, but also the biological condition. Maintaining soil health involves regular application of organic and mineral fertilizers, maintaining optimal conditions for soil microorganisms and preventing soil depletion. Introduction of crop rotation methods into practice allows to avoid depletion of certain soil elements and maintain its fertility. Mulching, on the other hand, helps to conserve moisture, reduces erosion and improves soil structure.

Water management is also a critical aspect of successful agricultural production. Traditional irrigation methods, such as widespread sprinkling, can lead to significant losses and inefficient resource allocation. The introduction of modern technologies such as drip irrigation and water management systems can optimize resource use, increasing efficiency and reducing losses. These technologies not only help in increasing the productivity of agricultural systems but also help in reducing the negative impact on the environment. For example, drip irrigation minimizes evaporation and runoff, allowing water to flow directly to the roots of plants for better growth and development [1-4].

Sustainable water resource management also encompasses practices for water conservation and pollution prevention. This may involve constructing rainwater harvesting reservoirs, implementing wastewater treatment technologies, and utilizing water-saving systems. These measures not only help conserve valuable resources but also support ecological balance, prevent soil degradation, and maintain biodiversity.

2 Materials and methods

Data mining techniques enable the identification of hidden patterns, trends, and relationships within large volumes of information, which is especially crucial in today's information-rich environment. These methods transform raw data into actionable insights that can be used for making informed decisions, forecasting future events, optimizing business processes, and developing strategies. Specifically, machine learning algorithms, statistical methods, and other analytical techniques allow experts to handle complex and diverse datasets, uncovering significant patterns and anomalies that might be overlooked in traditional analysis.

In this study, various data analysis methods were employed to deepen the understanding of the relationship between water availability and agricultural production indicators. Specifically, correlation analysis, clustering methods, and data modeling were used to provide a comprehensive view of how water resources impact the agricultural sector.

Correlation analysis, a fundamental tool in statistical analysis, determines the degree and direction of the relationship between two or more variables. In this research, correlation analysis was applied to explore the relationship between water availability and key agricultural indicators such as crop yield, production volumes, and planted areas. This helped to establish the strength and direction of these factors' interconnections [5-8].

Clustering methods were used to group objects into homogeneous clusters based on their similarities. In this context, clustering was applied to categorize regions or agricultural enterprises according to their water availability and its impact on agricultural production. Clustering revealed regions with similar water availability characteristics and assessed how these characteristics affect agricultural performance. This approach facilitated a deeper understanding of the spatial distribution of resources and their effects on agricultural production.

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3 Data structure

The dataset is divided into four thematic sets. The first set contains agricultural crop price indicators. This data includes five fields: District – production districts, represented by 10 units; Crop – agricultural crops, with 23 varieties; Market – sales nodes, with 24 names; Date – the price registration date, ranging from March 21, 2018, to May 18, 2019; Price (INR/quintal) – the price of agricultural crops, with the distribution illustrated in Figure 1.

№	Range	Share	Quantity	%
1	до 1323		0	0
2	1323: 1761		35	1
3	1761: 2199		712	15
4	2199: 2637		2546	53
5	2637: 3075		1405	29
6	3075: 3513		121	3
7	от 3513		0	0

Fig. 1. The distribution of the factor "Price (INR/quintal)"

The second dataset is dedicated to crop productivity levels. It includes the following factors:

1. District – production districts (10 units);
2. Crop – agricultural crops (23 varieties);
3. Season – growing season, represented by two types;
4. Area (hectares) – the area allocated for the crop, with its distribution across districts shown in Figure 3;
5. Yield (quintals) – the yield of the crop on the corresponding area, with the distribution of values shown in Figure 2(a);
6. Production (metric tons) – the mass of produced crop from the corresponding area, with the distribution of values shown in Figure 2(b).

№	Range	Share	Quantity	%
1	до 20.27		0	0
2	20.27: 26.01		72	7
3	26.01: 31.75		207	21
4	31.75: 37.48		227	23
5	37.48: 43.22		233	23
6	43.22: 48.96		165	17
7	48.96: 54.69		77	8
8	54.69: 60.43		19	2
9	от 60.43		0	0

(a)

№	Range	Share	Quantity	%
1	до 1728		0	0
2	1728: 3029		35	4
3	3029: 4330		193	19
4	4330: 5631		291	29
5	5631: 6932		254	25
6	6932: 8233		156	16
7	8233: 9534		59	6
8	9534: 10835		12	1
9	от 10835		0	0

(b)

Fig. 2. The distribution of values: a – factor "Yield (quintals)", b – factor "Production (metric tons)".

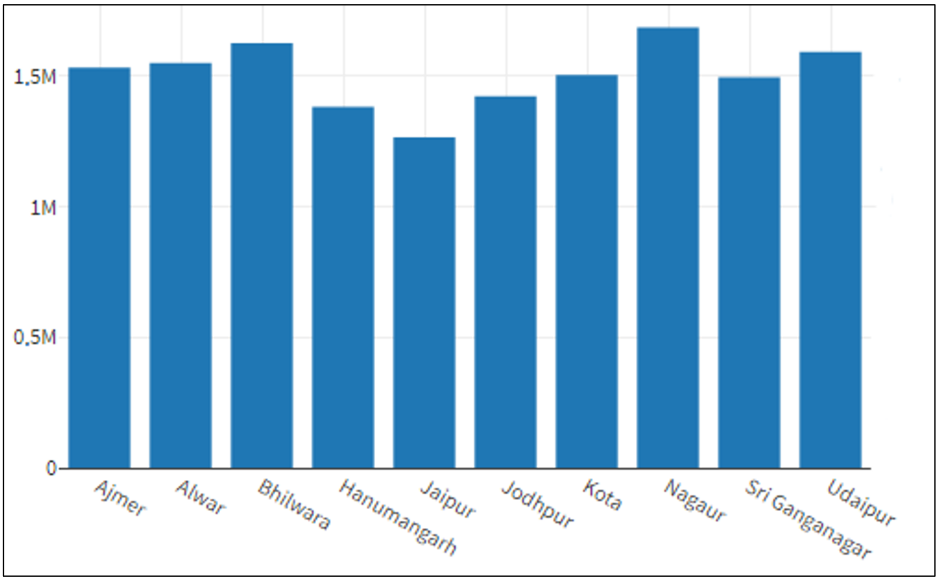


Fig. 3. The distribution of the factor "Area (hectares)" with respect to the factor "District."

The third dataset contains information on soil type and composition relative to agricultural production districts and is represented by the following fields:

1. District – production districts (10 units);
2. Soil Type – type of soil, with 8 attributes;
3. pH Level – soil pH level;
4. Organic Matter (%) – percentage of organic matter in the soil;
5. Nitrogen Content (kg/ha) – nitrogen content in the soil;
6. Phosphorus Content (kg/ha) – phosphorus content in the soil;
7. Potassium Content (kg/ha) – potassium content in the soil.

The distribution of soil composition values is provided in Table 1 and Table 2.

Table 1. The distribution of soil composition values, part 1.

Range	Quantity	%
pH Level		
5.899 : 6.519	28	3
6.519 : 7.149	220	22
7.149 : 7.779	455	46
7.779 : 8.409	259	26
8.409 : 9.038	38	4
Organic Matter (%)		
0.156 : 0.878	12	1
0.878 : 1.599	208	21
1.599 : 2.321	515	52
2.321 : 3.043	240	24
3.043 : 3.765	24	2
Nitrogen Content (kg/ha)		
11.99 : 18.75	12	1
18.75 : 25.50	188	19

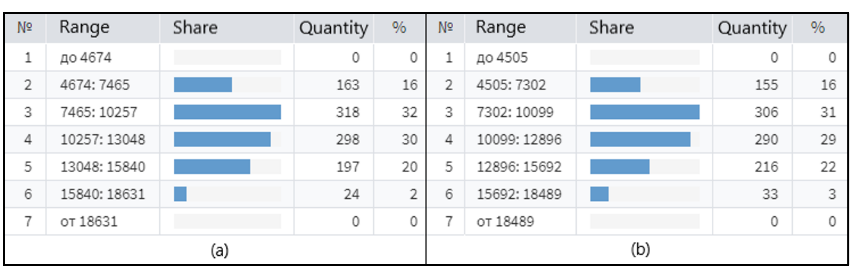
25.50 : 32.25	487	49
32.25 : 39.01	268	27
39.01 : 45.76	45	5

Table 2. The distribution of soil composition values, part 2.

Range	Quantity	%
Phosphorus Content (kg/ha)		
4.96 : 11.09	48	5
11.09 : 17.21	269	27
17.21 : 23.34	443	44
23.34 : 29.46	218	22
29.46 : 35.59	22	2
Potassium Content (kg/ha)		
24.12 : 30.23	23	2
30.23 : 36.34	202	20
36.34 : 42.45	476	48
42.45 : 48.57	266	27
48.57 : 54.68	33	3

The fourth dataset represents data on crop irrigation methods, as well as water consumption and availability in specific regions. This dataset includes the following factors:

- District – production regions (10 names);
- Crop – agricultural crop (23 names);
- Irrigation Method – irrigation method represented by 4 attributes;
- Water Consumption (liters/hectare) – water consumption, the distribution of which is shown in Figure 4(a);
- Water Availability (liters/hectare) – water availability, the distribution of which is shown in Figure 4(b).



№	Range	Share	Quantity	%
1	до 4674		0	0
2	4674: 7465		163	16
3	7465: 10257		318	32
4	10257: 13048		298	30
5	13048: 15840		197	20
6	15840: 18631		24	2
7	от 18631		0	0

(a)

№	Range	Share	Quantity	%
1	до 4505		0	0
2	4505: 7302		155	16
3	7302: 10099		306	31
4	10099: 12896		290	29
5	12896: 15692		216	22
6	15692: 18489		33	3
7	от 18489		0	0

(b)

Fig. 4. The distribution of values: a – factor "Water Consumption (liters/hectare, b – factor "Water Availability (liters/hectare)"

4 Results

Agricultural crops vary in their water requirements depending on their growth and development characteristics, the climatic conditions in which they are grown, and the properties of the soil. The main factors determining a plant's water needs include its life cycle,

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root system, ability to adapt to dry conditions, and water consumption at different growth stages.

Some crops require stable and sufficient moisture throughout the entire growing season, especially during critical periods such as flowering or fruiting. Other plants can adapt to less frequent watering and better withstand dry conditions due to deep roots or other adaptive mechanisms [9-13].

Therefore, the initial data have been supplemented with information on the water needs of the crops in question, as shown in Figure 5.

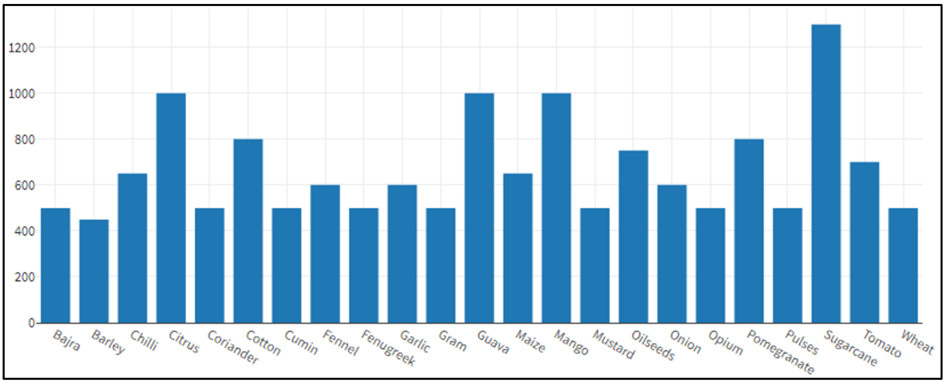

Fig. 5. Seasonal water requirements for agricultural crops (mm)

Based on the data on crop water requirements, two groups were formed:

1. Crops with lower water needs: Bajra, Barley, Coriander, Cumin, Fennel, Fenugreek, Garlic, Gram, Mustard, Onion, Opium, Pulses, Wheat;
2. Crops with higher water needs: Chilli, Citrus, Cotton, Guava, Maize, Mango, Oilseeds, Pomegranate, Sugarcane, Tomato.

The second group includes crops that require more than 600 mm of water per season, while the remaining crops are classified in the first group [14-16].

Figures 6 and 7 show the relationship between the average price and the month for crops with lower water needs and those with higher water needs, respectively [17-19]. Before constructing the graphs, the data was processed to remove outliers. This process revealed that, in general, there is no clear dependence of the average price on the month of registration. The relationship between the average price and the month is specific to each crop.

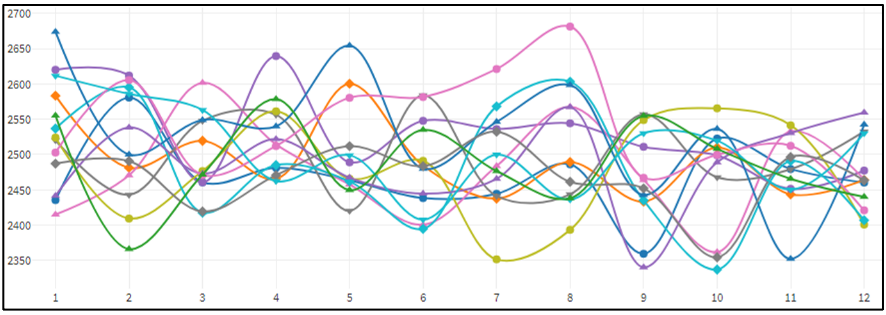

Fig. 6. The relationship between the average price and the month for crops with lower water needs

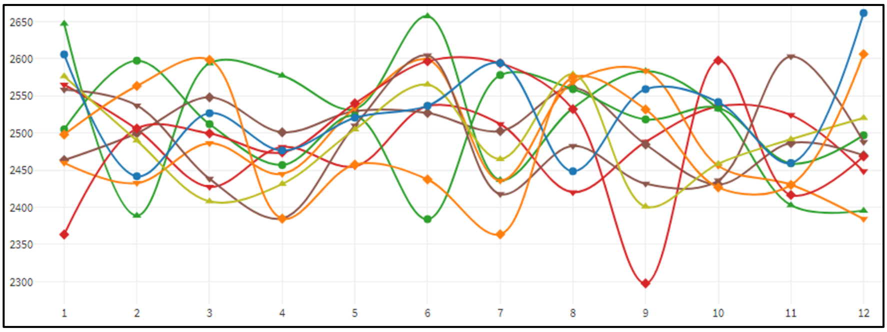

Fig. 7. The relationship between the average price and the month for crops with higher water needs

Correlation analysis for the dataset containing information on price and market showed a moderate correlation between District and Market. This suggests that while the choice of sales node may take the growing region into account, it is not a decisive factor [20, 21].

Additionally, the analysis, the results of which are presented in Figure 8, determined that the first dataset does not contain factors influencing price.

1	Crop	District	-0,02275434245
2	District	Crop	-0,02275434245
3	Date	Crop	-0,007357650523
4	Crop	Date	-0,007357650523
5	Price (INR/quintal)	Crop	-0,003020659813
6	Crop	Price (INR/quintal)	-0,003020659813
7	Date	District	0,006025447951
8	District	Date	0,006025447951
9	Market	Crop	0,0097988052
10	Crop	Market	0,0097988052
11	Date	Market	0,0142358288
12	Market	Date	0,0142358288
13	Price (INR/quintal)	Date	0,01850470913
14	Date	Price (INR/quintal)	0,01850470913
15	Price (INR/quintal)	District	0,02008611168
16	District	Price (INR/quintal)	0,02008611168
17	Price (INR/quintal)	Market	0,02305554694
18	Market	Price (INR/quintal)	0,02305554694
19	Market	District	0,4015006188
20	District	Market	0,4015006188

Fig. 8. Results of the correlation analysis of the price dataset

Seasonal conditions have a significant impact on crop yield. Temperature, precipitation, and day length influence plant growth and development. Optimal conditions contribute to high yields, while extreme temperatures and either a lack of or excess of moisture can reduce productivity. Seasonal changes in soil composition also play a role, affecting the availability of nutrients [22-25].

The Kharif and Rabi seasons are key periods in Indian agriculture, each with its own characteristics and importance for agricultural production. The Kharif season begins with the onset of the monsoon, typically in June, and lasts until October. This season is characterized by abundant rainfall, making it ideal for growing crops that require a lot of water. Major crops grown during this period include rice, maize, soybeans, and cotton. Plants in this season often face issues with diseases and pests, necessitating active use of plant protection measures [26].

Following the monsoon, the Rabi season begins, lasting from November to April. This season is drier and cooler, creating optimal conditions for many other crops. During this time, farmers can grow crops such as wheat, barley, peas, and mustard [27]. A key feature of the Rabi season is that it requires systematic irrigation, as precipitation is insufficient. Effective water use and proper soil management are crucial for a successful harvest in this season.

The correlation analysis of the yield dataset revealed a relationship between the factor "Production (metric tons)" and "Area (hectares)." The correlation coefficient in this case was 0.642, indicating a significant dependency of the yield on the area. Therefore, when analyzing growing seasons, it is important to consider the yield data, which represents the ratio of produced output to the area [28,29].

Figure 9 shows the average yield levels of crops depending on the season. It is evident that 15 out of 23 crops have higher yields in the Rabi season, which is characterized by drier weather, compared to the Kharif season. In both groups, there are 4 crops (8 in total) whose yields are higher in the Kharif season according to the data. The first group includes Barley, Bajra, Gram, and Mustard, while the second group consists of Tomato, Chilli, Citrus, and Sugarcane, which is not explained by the crops' water needs.

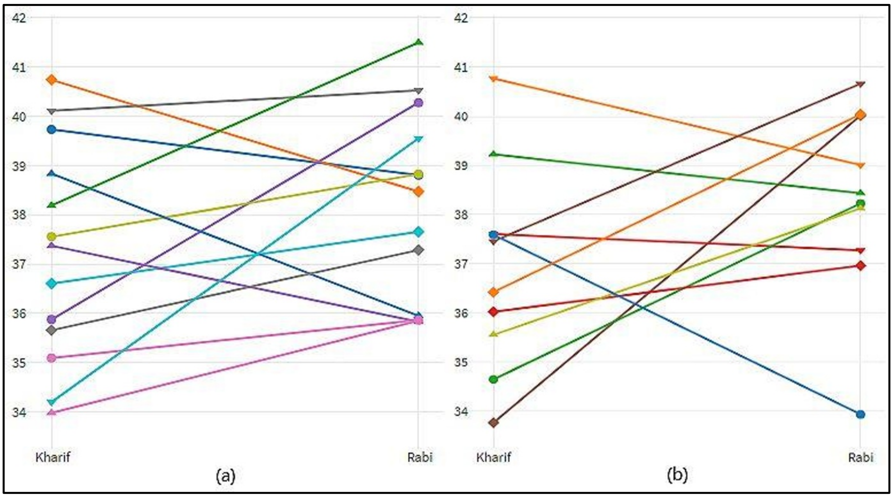

Fig. 9. Average crop yield by seasons: a – crops with lower water requirements, b – crops with higher water requirements

Soil substances play a key role in the health and productivity of agricultural crops. Essential elements such as nitrogen, phosphorus, and potassium are necessary for plant growth and development. Nitrogen promotes the formation of green biomass and enhances photosynthesis, phosphorus is needed for root development and flowering, while potassium supports overall metabolism and strengthens plant cells. Additionally, micronutrients like iron, zinc, and copper are also important for the proper functioning of plant enzyme systems [30, 31].

Soil quality also depends on its structure and ability to retain moisture. Well-structured soil with adequate organic matter provides better root aeration and prevents waterlogging, reducing the risk of plant diseases [32-35]. The impact of soil on crops also includes its acidity: excessively high or low acidity can hinder nutrient absorption. Therefore, regular fertilization and pH adjustment help maintain optimal conditions for crop growth.

Table 3. Results of the cluster analysis

Cluster	Total	Cl 0	Cl 1	Cl 2	Cl 3	Cl 4	Cl 5	Cl 6
Support	100%	17%	18%	14%	13%	13%	13%	13%
District	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Crop	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Irrigation Method	100.0	100.0	99.99	100.0	100.0	100.0	100.0	100.0
Soil Type	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
Water Consumption (liters/hectare)	52	65	70	42	42	42	42	62
Water Availability (liters/hectare)	53	66	71	42	42	43	42	62
pH Level	38	40	38	36	51	67	34	38
Organic Matter (%)	34	33	32	42	51	38	33	39
Nitrogen Content (kg/ha)	30	25	28	53	28	27	28	30
Phosphorus Content (kg/ha)	33	28	31	29	37	34	71	29
Potassium Content (kg/ha)	35	44	33	43	35	34	35	44

Correlation analysis did not reveal dependencies between soil composition and other factors. Table 3 presents the results of the cluster analysis, which identified the following significant factors in general: District, Crop, Irrigation Method, and Soil Type. For Cluster Cl 1, the significant factors include Water Consumption (liters/hectare) and Water Availability (liters/hectare), which have a high correlation with each other. For Cluster Cl 5, the significant factor is Phosphorus Content (kg/ha). This indicates that soil composition factors are not highly significant when it comes to water resources.

Conclusion

Water is the foundation of agriculture, providing vital conditions for plant growth. With global climate change and increasing population needs, water resource management becomes critically important. Efficient water use impacts not only crop yield but also product quality.

Modern irrigation technologies, such as drip irrigation, help optimize water consumption and reduce waste. Additionally, protecting water resources from pollution and monitoring their quality are crucial.

This study conducted a comprehensive analysis of the impact of water resource availability on the agricultural sector, focusing on several key aspects. The research covered the evaluation of soil composition and its effect on crop yield and productivity, as well as the effectiveness of various irrigation methods. Special attention was given to seasonal fluctuations in crop production and their dependence on water resources. The analysis also included economic indicators, such as crop prices and water resource costs.

Data mining methods allowed for a deeper exploration of the impact of water availability on the agricultural sector. Correlation analysis revealed that while water availability has a significant influence on crop yield and productivity, it is not the sole determining factor. In some cases, soil composition and agronomic practices emerged as more critical factors. Factor analysis identified key elements affecting yield, including not only water availability but also soil type, climatic conditions, and agronomic practices. It was established that although water does affect agricultural production, it is not always the primary determining factor.

Data clustering revealed groups of factors and conditions that collectively have a complex impact on agricultural outcomes. This confirms that optimizing agricultural activities requires considering a multitude of variables, not just water availability.

The study's results indicate that while water resource availability has a noticeable effect on agricultural production, it is neither the only nor the most crucial factor. To achieve the best results, it is necessary to consider a range of factors, including soil characteristics, climatic conditions, agronomic practices, and economic aspects.

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