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# الأقلمة الزراعية المناخية وجدول الري الأمثل لولاية أندرا براديش، الهند

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## ملخص:

**هدف الدراسة:** واحدة من أكثر الطرق المفيدة لتحديد قدرات الأراضي التي يجب حجزها لأفضل الأشكال وأكثرها إنتاجية هي الأقلمة الزراعية المناخية أو تقسيم المناطق (ACZ). يقسم إطار عمل ACZ العالم إلى مناطق بناءً على التضاريس والتربة واستخدام الأراضي والمناخ. يقدم هذا البحث أقلمة زراعية مناخية ACZ لولاية أندرا براديش (AP) باستخدام خوارزمية تصنيف IHW-DNN. تقسم خوارزمية التصنيف المناطق الزراعية المناخية لولاية أندرا براديش AP إلى سبع مناطق بناءً على بعض خصائص المناطق الثلاث لـ AP. في البداية، تجمع بيانات الإدخال من المواقع المتاحة علناً لإجراء التصنيف. تستخرج الميزات الخاصة لولاية AP؛ مثل الجغرافيا الطبيعية، وخصائص التربة، والمعلومات الجيولوجية، وطول فترة النمو، والأنواع المناخية، والنتح التبخري المحتمل، وأنماط المحاصيل. تصنف ولاية AP إلى سبع مناطق زراعية مناخية بناءً على هذه الميزات. ثم تقدّم جدولة الري للمناطق المصنفة باستخدام خوارزمية التحسين الأمثل، وهي خوارزمية سرب الخنفساء التي تستخدم قيمة تناسب جديدة لإعطاء مجموعة مثالية من جداول الري للمحاصيل في ولاية AP. تجرى التجارب لتحديد مدى فعالية الطرق المقترحة، وتشير النتائج إلى أن الطرق المقترحة فعالة.

**الكلمات المفتاحية:** الأقلمة الزراعية المناخية، تحديد المناطق المناخية الزراعية، ولاية أندرا براديش، جدولة الري، تحسين سرب الخنفساء الأمثل (**BSO**)، الشبكة العصبية العميقة (**DNN**)

# Agro-climatic Regionalization and Optimal Irrigation Scheduling for the State of Andhra Pradesh, India

*Gesatya Sirnivasa Opinnath*

**Abstract**

**Objective:** One of the most useful methods for identifying land capabilities to be reserved for the best and most productive forms of productivity is agro-climatic regionalization or zoning (ACZ). The ACZ framework divides the world into zones based on topography, soil, land use, and climate. **Methods:** This paper presents an ACZ of Andhra Pradesh (AP) using a classification algorithm IHW-DNN. The classification algorithm classifies the agro-climatic zones of AP into seven zones based on some characteristics of the three regions of AP. Initially, the input data is collected from the openly available sites to perform classification. The features, such as physiography, soil characteristics, geological information, and length of the growing period, climatic types, potential evapo-transpiration, and cropping patterns are extracted for the regions of the AP. **Results:** The AP is classified into seven agro-climatic regions based on the features. Then the irrigation scheduling of the classified zones is presented using an optimization algorithm, namely beetle swarm algorithm that uses a novel fitness value for giving an optimal set of irrigation schedules for the crops in the zones of AP. **Conclusion:** Experiments are carried out to determine the efficacy of the proposed methods, and the results indicate that the proposed methods are effective.

**Keywords:** Agro-climatic Regionalization, Agro-climatic Zoning, Andhra Pradesh, Irrigation Scheduling, Beetle Swarm Optimization (BSO), Deep Neural Network (DNN)

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## 1. Introduction

Agriculture plays a vital role in India’s economy with about 18% share in GDP at 2011–2012 prices, 11% of exports, and 54.6% share in total employment or workforce. Agriculture is one of the most affected sectors by a variety of factors such as climatic changes, soil characteristics, seasonal changes, and so on. Agriculture is one of the most vulnerable sectors to the impacts and threats of global climate change due to its inherent vulnerability to weather conditions. (PIB Delhi, 2021).

Yield sensitivity to weather anomalies could be a major concern seeable of climate-smart farming and is predicted to possess a negative result on crop production particularly in vulnerable areas, thereby, moving the country’s food security. (World Bank, 2020). The impact of temperature change on agricultural production will adversely influence world food security in four ways: food availableness, food accessibility, food utilization, and food system stability. Most of the agro-climatic assessments up to now are supported point/field-scale studies. Studies of food security beneath a dynamic climate associated extreme weather highlight an increasing demand for big spatial scale crop yield simulations (UNFAO, 2015). Due to high-intensity downfall and temperature, these regions are extremely vulnerable. Crop water demand is already terribly high and increasing unceasingly. (IPCC Fourth Assessment Report: Climate Change, 2007). Water demand and water handiness per square measure are the two main parameters for effective water resources management, and water inadequacy is the main driver for water resources coming up with an optimization (Tzanakakis et al., 2020). Inadequate downfall causes water insufficiency. Tiny grains are widely grown in those extreme conditions in many locations with little rain and high temperatures (Praba et al., 2009). Agro-climatic indices have historically been derived from actual meteorological data to better describe the relationship between the weather and crop growth and to aid in agricultural decision-making. (Mathieu, 2018). Rather than trying to predict absolute yield changes based on present or future management and cultivars, an approach is used based on changes in the conditions for agriculture, such as the length of the growing season and the need for irrigation and subsurface drainage. (Liliane, 2020). Elevated temperature accelerates the development of most crops and leads to shorter crop growth periods. (Zhao, 2017). However, it is difficult to extend and generalize the results because of different soil types, irrigation regimes, plant rooting patterns and salinity tolerances, depth and fluctuations of water tables, and climatic conditions. (DongyangRen, 2018). A tactical approach to bypass drought and other general adverse climate conditions, as part of a strategy to support an efficient agricultural production based on an understanding of spatial and temporal climate variability. (OECD, 2012). Extreme weather and climate events vary from place to place, occurring first at the local level and locally affecting people, but with impacts then cascading to different extents at the national and international levels. (A Raza, 2019). This paper considers all the mentioned parameters for agro-climatic classification, which uses the deep learning algorithm and presents for agro-climatic regionalization of Andhra Pradesh (AP) state. AP, state of India, is located in the southeastern part of the subcontinent; it lies between 12°41' and 19.07°N latitude and 77° and 84°40'E longitude, and it is bordered by Telangana, Chhattisgarh, and Orissa in the north, the Bay of Bengal in the East, Tamil Nadu in the south and Karnataka in the west. Based on physiography, the state may be divided into three main regions: i) Coastal AP, ii) Telangana, and iii) Rayalaseema. There are several sub-zones that come under the three regions that are represented as agro-climatic zones of AP.

In addition, improving potential production and reducing local yield gaps is crucial to continuous crop productivity gains under increasingly limited cultivation lands. (Ittersum, 2013). Proper calibrations and validations were required for its application over a wide range of varieties cultivated over various agro-climatic zones in India. (Ahmed, 2016). in water-scarce regions, surface drip irrigation, subsurface drip irrigation, alternate-rows irrigation, and other water-saving methods are widely implemented. (Nikolaou, 2020). It is empirically verified that in the developing countries or regions where agriculture is the mainstay of people's livelihood, improvement of agricultural productivity is the critical entry-point for an effective reduction in the level of poverty. (National Commission on Farmers, 2006). This paper also presents an optimal irrigation scheduling mechanism for the classified zones of AP using the Beetle Swarm Optimization (BSO) algorithm.

The draft structure of this paper is systematized as follows: Section 2 surveys the associated works regarding the proposed method; Section 3 proffers a brief elucidation of the proposed work; Section 4 explores the experimental outcome; and Section 5 exhibits the conclusion.

## 2. Related Work

(Huang et al., 2019). studied the regional climate–yield relationship for winter oilseed rape in Jiangsu province, southeast China. The correlations between oilseed rape yield and climate variables indicated that average Temperature Difference (TD), total Rainfalls (RF), total Rainy Days (RD), total Sunshine Hours (SH), and average Relative Humidity (RH) in spring were the key agro-meteorological indicators significantly affecting yield. By using Principal Component Analysis (PCA), this province could be classified into four agro-climatic regions: north, central-north, central-south, and south Jiangsu, respectively. Compared to the northern areas, the relatively stronger decreasing trends of RF, RD, and RH during 1961–2012 were detected in the southern areas, which had increased oilseed rape yield by up to 0.68%, 1.44%, and 5.68%, respectively. In this area, a pre-warning system of oilseed rape water logging disasters was not detected in this method.

(Nabati, 2020). In this research, data preparation in a GIS environment and membership function defined in Fuzzy Inference System (FIS) then used weighted linear combination (WLC) for determining parameters weight for agro-ecological zoning of chickpea in semi-arid regions of Iran that includes climatic, topography, soil, and land use parameters. The results also showed that agro-climatic zoning and agro-land use zoning have an essential role in determining the optimal areas for chickpea production in rain-fed and irrigated conditions. The use of GIS and fuzzy inference system improved the accuracy of spatial data, more productive analysis, and enhanced data access. More varieties of crops were not used in this method.

(Busettoa, 2019). developed a Pheno Rice algorithm to track recent variations of rice cultivation practices along the Senegal River Valley over a 14-year period (2003–2016). The spatial and temporal variations of rice cultivated area, crop establishment and harvesting dates, length of the season, and cropping intensity were mapped for both the dry and the wet seasons. The analysis also revealed a statistically significant increase in the length of the dry season since 2006 and a corresponding decrease in the length of the wet season. The study demonstrated that multiannual maps of parameters, such as harvesting dates and crop intensity, might allow depicted variations in the characteristics of rice production systems in Africa and across the world. However, the PhenoRice algorithm permitted monitoring spatial-temporal changes in rice agro-practices with unprecedented accuracy and spatial resolution.

(Borges Valeriano et al., 2018). Introduced a correlation method based on correlations between monthly water deficit (DEF) during the crop cycle and annual yield and performed a multivariate cluster analysis on these correlations. The correlation method classified those areas as high-producing regions and expanded them into other areas. This method, called the correlation method, determined agro-climatic zones with more efficiency than a traditional agro-climatic zone-based on the range of meteorological elements. The correlation method identified all known traditional coffee regions in the state of Sao Paulo and expanded them to new potentials. This method allowed for the identification of correlated monthly DEFs with yield levels within each agro-climatic zone. This method is expensive and time-consuming to achieve an outcome.

(Bulgakov et al., 2018). Introduced the separation of agro-climatic areas for optimal crop growth within the framework of the natural–agricultural zoning of Russia. Overall, 64 agro-climatic areas have been separated in Russia. They were specified by the kind of soil and agro-climatic conditions and by the kinds of crops recommended for cultivation. Climatic conditions of the areas and soil suitability for crop growth without damage to the soil cover and the environment were to be considered in decisions on optimal land uses. It was also helpful for terrain and remote sensing monitoring of soil fertility on arable lands and soil ecological monitoring. However, less accuracy causes the yields to be low, and the cost of production was high because of the unfavorable soil and climatic conditions.

(Singh et al., 2019). Studied the detailed analysis to understand the changes in rainfall patterns and characteristics at a regional scale on an agro-climatic zone basis in the mid Mahanadi river basin. Most of the agro-climatic zones were found to have significant decreasing trends in the magnitude of rainfall during the non-monsoon season. The results of this indicated a climate change signal at the regional scale that would help the policymakers and water managers to identify the critical agro-climatic zones in the mid-Mahanadi river basin for the formulation of efficient water resources management and planning strategies, particularly for the major crops of the rain-fed agriculture regions. A short study region was experimented.

## 3. Proposed Methodology

To maximize the production from the available resources and prevailing climatic conditions, need-based, location specific technology needs to be generated. Delineation of agro-climatic zones based on soil, water, rainfall, temperature etc. is the first essential step for sustainable production. In this paper, an agro-climatic regionalization of AP has been presented with the help of HWI-DNN. For classifying the agro-climatic zoning of AP, the paper uses the publicly available database to extract the features. Generally, the AP is divided into three main regions: (i) Coastal Andhra Pradesh (ii) Telangana, and (iii) Rayalaseema. The features, such as physiography, soil characteristics, geological information, length of the growing period, climatic types, potential evapo-transpiration, and cropping patterns are extracted from the districts of AP, which come under the three main regions of AP and given as an input to the neural network for the classification. The HWI-DNN classifies the agro-climatic zoning of AP into nine zones based on the trained features. The seven zones classified by the proposed method are Krishna-Godavari, southern, Southern Telangana, High Altitude & Tribal areas, North Coastal, North Telangana, and Scarce Rainfall. The paper also presents irrigation planning for the classified zones of AP in an optimal manner. The architecture of the proposed method is shown in figure 1.

**Fig A.**
*Geographical Location of the Study Area*

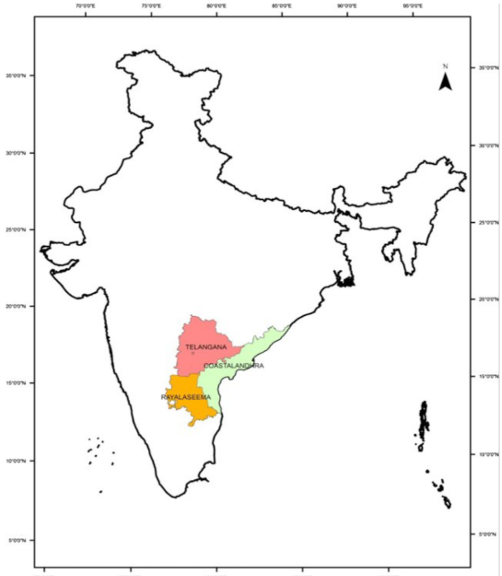



**Fig B.**
*Administrative Divisions of the Study Area*

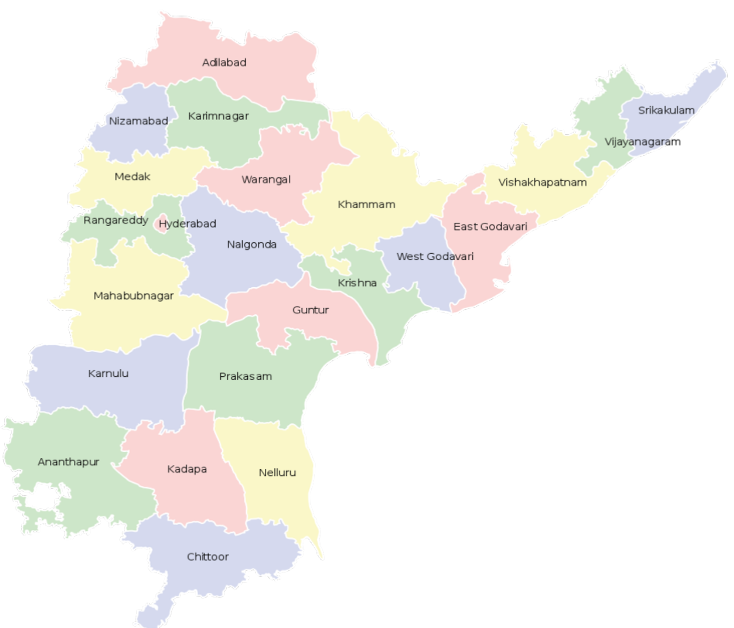
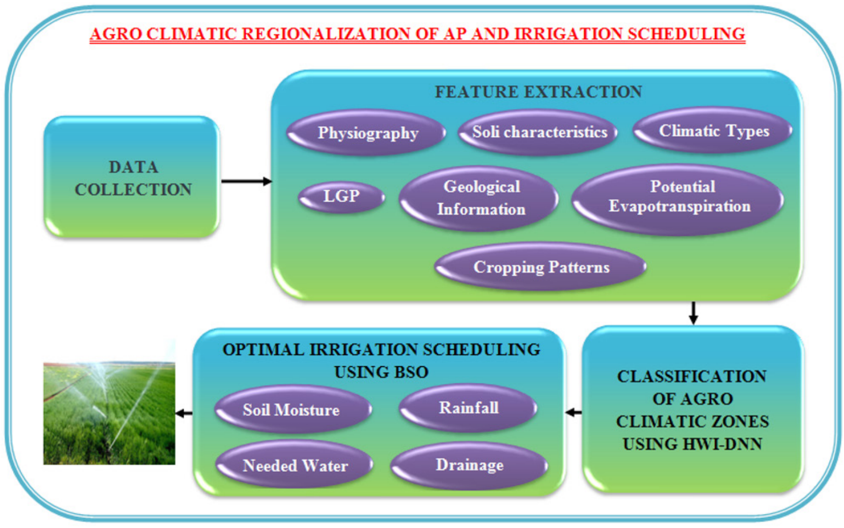


**Figure 1.**
*Architecture of the proposed method*




### 3.1 Data Collection

The first phase of the proposed method was data collection, and the paper data was collected from publicly available databases.

### 3.2 Feature Extraction

After data collection, the features were extracted from the dataset. The features that were extracted involved physiography, soil characteristics, geological information, length of the growing period (LGP), climatic types, potential evapo-transpiration (PET), and cropping patterns. Each of these features is defined as follows.

#### 3.2.1 Physiography

Physiography is the subfield of geography that studies physical patterns and processes of the three regions of the AP. It aims to understand the forces that produce and change rocks, oceans, weather, and global flora and fauna patterns.

#### 3.2.2 Soil characteristics

All soils contain mineral particles, organic matter, water, and air. The combinations of these determine the soil's properties, such as texture, structure, porosity, chemistry, and color.

### 3.2.3 Geological Information

Geological information can show many kinds of data on one map, such as streets, buildings, and vegetation of the particular region. This enables to see, analyze, and understand patterns and relationships more easily.

#### 3.2.4 Length of the growing period (LGP)

(Merugu, 2015). The LGP is a useful feature for calculating agricultural potential, and it can be used as a criterion for classifying areas and roughly determining crop cycle lengths. The calculation of the growing period is based on a simple water balance model, comparing precipitation with potential evapo-transpiration PET, using monthly values. Totally, three kinds of growing periods take place: A normal growing period is defined as one when there is an excess of precipitation over a PET (i.e. a humid period), and such a period meets the full evapo-transpiration demands of crops and replenishes the moisture definite of the soil profile; An intermediate growing period is defined as one in which precipitation does not normally exceed PET but does for part of the year; No growing period occurs when temperatures are not conducive to crop growth.

#### 3.2.5 Climatic types

(Guhathakurta et al., 2020). The climate of Andhra Pradesh varies considerably, depending on the geographical region. Summers last from March to June. In the coastal plain, the summer temperatures are generally higher than the rest of the state, with temperature ranging between 20 and 41 °C (68 and 106 °F). July to September is the season for tropical rains; about one-third of the total rainfall is brought by the northeast monsoon. October and November see low-pressure systems and tropical cyclones form in the Bay of Bengal which, along with the northeast monsoon, bring rains to the southern and coastal regions of the state. November, December, January, and February are the winter months in Andhra Pradesh. Since the state has a long coastal belt, winters are not very cold. The range of winter temperature is generally 12 to 30 °C (54 to 86 °F). Lambasingi in Visakhapatnam district is also nicknamed as the "Kashmir of Andhra Pradesh" due to its relatively cool climate when compared to other areas and the temperature ranges from 0 to 10 °C (32 to 50 °F).

### 3.2.6 Potential evapotranspiration (PET)

Potential Evaporation (PE) or Potential Evapo-transpiration (PET) is defined as the amount of evaporation that would occur if a sufficient water source was available. If the actual evapo-transpiration considers the net result of atmospheric demand for moisture from a surface and the ability of the surface to supply moisture, then PET is a measure of the demand side.

### 3.2.7 Cropping patterns

(Mouzam, 2015). Cropping pattern refers to the proportion of land under cultivation of different crops at different points of time. This indicates the time and arrangement of crops in a particular land area. The major crops grown in the State in the Kharif season are paddy, cotton and ground nut, and in the Rabi season the major crops are paddy and sunflower. The other main crops in the state are black gram, sugarcane, and tobacco.

### 3.3 Agro-Climatic Classification

After extracting the features, they are inputted into the HWI-DNN for agro-climatic classification. A Deep Neural Network (DNN) is an Artificial Neural Network (ANN) with multiple layers between the input and output layers. There are different types of neural networks, but they always consist of the same components: neurons, synapses, weights, biases, and functions. In DNN, weights represent the strength of connections between units in adjacent network layers. The linear transformation of these weights and the values in the previous layer passes through a non-linear activation function to produce the values of the next layer. This process happens layer to layer during the forward propagation; through back propagation, the optimum values of these weights can be found out so as to produce accurate outputs given an input. Improperly initialized weights can negatively affect the training process by contributing to the vanishing or exploding gradient problem. With the vanishing gradient problem, the weight update is minor and results in slower convergence, the optimization of the loss function becomes slow and in a worst-case scenario, may stop the network from converging altogether. To address this issue, the proposed method uses the He Weight Initialization (HWI) for DNN, which considers the size of the network (number of input and output units) while initializing weights and serve as good starting points for initialization and mitigating the chances of exploding or vanishing gradients. It sets the weights neither too much bigger than 1, nor too much less than 1. So, the gradients do not vanish or explode too quickly. It helps to avoid slow convergence. This HWI based DNN is named HWI-DNN. The algorithmic procedure of DNN is given as follows:

Step 1: Given the extracted features of the three regions of AP as an input to the HWI-DNN

Step 2: Initialize the weights' values for each input data (extracted features) that is given in the input layer using the HWI function and assigning it to the hidden layer neurons as well as the output layer neurons. Maintain weight for all neurons of the input layer.

Step 3: Evaluate the output of the hidden layer using the equations below. The proposed method uses the five hidden layers between the input and output layer.

$$H_{1i} = B_{1i} + \sum_{i=1}^{N} M_i W_{1i} \tag{i}$$

$$H_{2i} = B_{2i} + \sum_{i=1}^{N} H_{1i} W_{2i} \tag{ii}$$

$$H_{3i} = B_{3i} + \sum_{i=1}^{N} H_{2i} W_{3i} \tag{iii}$$

$$H_{4i} = B_{4i} + \sum_{i=1}^{N} H_{3i} W_{4i} \tag{iv}$$

$$H_{5i} = B_{5i} + \sum_{i=1}^{N} H_{4i} W_{5i} \tag{v}$$

Where $B_{1i}$, $B_{2i}$, $B_{3i}$, $B_{4i}$ and $B_{5i}$ denote the bias values of the first, second, third, fourth, and fifth hidden layers, $W_{1i}$, $W_{2i}$, $W_{3i}$, $W_{4i}$ and $W_{5i}$ denote the weight values of the hidden layers 1, 2, 3, 4, and 5; and $F_i$ refers to the input feature values from the previous section. The bias values of the DNN are taken randomly within the range [0.1]. The weight values of the DNN are initialized. The 'He' initialization function initializes the weight values randomly but with the following variance:

$$v^2 = 2/N$$

Step 4: To find the final output unit, the final hidden layer is multiplied with the weight of the same hidden layer's output, which is given in the equations below:

$$M_i = B_{6i} + \sum_{i=1}^{N} H_{5i} W_{6i} \tag{vi}$$

Where, $W_{6i}$ denotes the weight of the final hidden layer's output, and $B_{6i}$ denotes the bias value of the final hidden layer's output, and $M_i$ denotes the output unit, which specifies the output of 7 classes of data: Krishna-Godavari, southern, Southern Telangana, High Altitude & Tribal areas, North Coastal, North Telangana, and Scarce Rainfall.

Step 5: Estimate the activation function of the output layer and recognize the learning error as follows:

$$A_F = \frac{1}{1+e^{-M_i}} \tag{vii}$$

$$L_E = \sum T_i - M_i \tag{viii}$$

Where, $L_E$ signifies the error rate, $T_i$ denotes the target output value, and $M_i$ is referred to as the actual output value. Table 1 below shows the classified agroclimatic zones of AP with their specific parameters.

**Table 1.**

*Agro-Climatic Zones of AP*

| Agro climatic zones | Districts covered | Rainfall (mm) | Temperature (°C) | | Soil Type | Crops grown |
|---|---|---|---|---|---|---|
| | | | Max | Min | | |
| Krishna – Godavari | East Godavari Part, West Godavari, Krishna, Guntur, and contiguous areas of Khammam, Nalgonda and Prakasam. | 800-1100 | 32-36 | 23-24 | Deltaic alluvium, red soils with clay, red loams, coastal sands and saline soils | Paddy, Groundnut, Jowar, Bajra, Tobacco, cotton, chilies, Sugarcane and Horticultural Crops |

**Cont. Table 1.**

*Agro-Climatic Zones of AP*

| Agro climatic zones | Districts covered | Rainfall (mm) | Temperature (°C) | | Soil Type | Crops grown |
|---|---|---|---|---|---|---|
| | | | Max | Min | | |
| North Coastal | Srikakulam, Vizianagaram, Visakhapatnam and uplands of East Godavari dist. | 1000-1100 | 33-36 | 26-27 | Red soils with clay base, pockets of acidic soils, laterite soils | Paddy, Groundnut, Jowar, Bajra, Mesta, Jute, Sun hemp, Sesame, Black gram and Horticultural Crops |
| Southern | Nellore, Chittoor, Southern parts of Prakasam and Cuddapah and Eastern parts of anantapur | 700-1100 | 33-46 | 23-25 | Red loamy soils, Shallow to moderately deep | Paddy, Groundnut, cotton Sugarcane. Millets and Horticultural Crops |
| North Telangana | Adilabad, Karimnagar, Nizamabad, Medak (Northern part), Warangal (Except N.W.Part), Eastern tips of Nalgonda and Khammam | 900-1500 | 30-37 | 21-25 | Chalkas, Red sandy soils, Dubbas, Deep Red loamy soils, Very deep black cotton soils | Paddy, Sugarcane, Castor, Jowar, Maize, Sunflower, Turmeric, Pulses and Chilies |

**Cont. Table 1.**

*Agro-Climatic Zones of AP*

| Agro climatic zones | Districts covered | Rainfall (mm) | Temperature (°C) | | Soil Type | Crops grown |
|---|---|---|---|---|---|---|
| | | | Max | Min | | |
| Southern Telangana | Hyderabad, Rangareddy, Mahabubnagar (except southern border), Nalgonda (except North eastern border), Medak (Southern parts), Warangal (North Western Part). | 700- 900 | 28-34 | 22-23 | Red earth with loamy sub soil (Chalkas) | Paddy, Sunflower, Safflower, Grapevine, Sorghum, Millets, Pulses and Orchard crops |
| Scarce rainfall | Kurnool, Anantapur, Prakasam (western parts), Cuddapah (Northern part), Mahabubnagar (Southern border). | 500-750 | 32-36 | 24-30 | Red earths with loamy soils (Chalkas), red sandy soils and black cotton soils in pockets | Cotton, Korra, Sorghum, Millets, Groundnut, Pulses, Paddy |
| High altitude and Tribal areas | Northern borders of Srikakulam, Vizianagaram and Visakhapatnam, East Godavari and Khammam. | >1400 | | | | Horticultural Crops, Millets, Pulses Chilies, Turmeric and Pepper |

### 3.4 Irrigation Scheduling

After the identification of agro-climatic zones of AP, the irrigation scheduling for the identified zones is performed using an optimization algorithm. There are many different types of irrigation systems, depending on how the water is distributed throughout the field.

Some main types of irrigation systems include:

**Surface irrigation:** Water is distributed over and across land by gravity, no mechanical pump involved.

**Localized irrigation:** It applies water directly where the plant is growing thus minimizing water loss through evaporation from the soil.

**Drip irrigation:** A type of localized irrigation that has the potential to save water and nutrients by allowing water to drip slowly to the roots of plants, either from above the soil surface or buried below the surface.

**Sprinkler irrigation:** This method applies water in a controlled manner based on rainfall. The water is distributed through a network that may consist of pumps, valves, pipes, and sprinklers. Irrigation sprinklers can be used for residential, industrial, and agricultural usage.

**Manual irrigation:** Water is distributed across land through manual labor and watering cans. This system is very labor intensive.

When water supplies are adequate, irrigation can dramatically increase crop yield. Different irrigation systems are suited to different soils, climates, crops, and resources. This paper uses an optimal version of sprinkler irrigation system; in this method, the device rotates around a pivot, in a circular path, and crops are watered with sprinklers as the machine moves. Also, this method can be integrated with multi-depth sensors for measuring and monitoring the conditions of the soil. Therefore, an optimal solution can be reached through these approaches for minimizing the use of energy and water. The optimization algorithm used is the Beetle Swarm Algorithm (BSA). BSA is proposed by combining the beetle foraging mechanism with the group optimization algorithm. The optimal irrigation scheduling using BSA is implemented by introducing a novel fitness function. The BSA considers the parameters, such as soil moisture, water content, rain fall, drainage in the specified zone for scheduling the irrigation for the crops grown in the zone. The BSO combines these parameters by iteration operation, and a Pareto solution set is obtained through iteration. This Pareto solution set includes several preferable irrigation schedules. Firstly, the fitness for the BSO is evaluated by considering the following parameters:

Let consider $P=(k, k+1, k+2,...K)$ be planting period, and it varies from one plant to another and can be measured with any usual temporal unit in which is the planting time and is the harvest time. $N_W=(w_i, w_{i+1}, w_{i+2},... wK)$

is needed water, and it refers to the water lost through evapotranspiration, $P=(p_i, p_{i+1}, p_{i+2}, ...pK)$ is efficient rain, $WR_{max}=(wr_i, wr_{i+1}, wr_{i+2}, ... wrK)$ is maximal useful water reserve $WE_{max}=(we_i, we_{i+1}, we_{i+2}, ... weK)$ is easily used water reserve, $Q=(q_i, q_{i+1}, q_{i+2}, ...qK)$ is soil moisture, and $G=(g_i, g_{i+1}, g_{i+2}, ...gK)$ is irrigation water. These values are the decision variables of the optimization algorithm. $C=(c_i, c_{i+1}, c_{i+2}, ...cK)$ is drainage water, in which:

$$\frac{\delta w}{\delta k}=\frac{\delta p}{\delta k}+\frac{\delta q}{\delta k}+\frac{\delta g}{\delta k}-\frac{\delta c}{\delta k} \quad \text{(ix)}$$

Based on the above parameters, the fitness is evaluated. The aim of the fitness function is to minimize

$$F=\sum_{i=k}^{K}\lambda_1 p_i+\lambda_2 q_i+x_i \quad \text{(x)}$$

Subject to

$$\sum_{i=k}^{K}x_i\leq G \quad \text{(xi)}$$

$$x_i\geq we_i-p_i-q_i+c_i \quad \text{(xii)}$$

$$x_i\leq wr_i-p_i-q_i+c_i \quad \text{(xiii)}$$

$$p_i\geq we_i-x_i-q_i+c_i \quad \text{(xiv)}$$

$$p_i\leq wr_i-x_i-q_i+c_i \quad \text{(xv)}$$

$$q_i\geq we_i-p_i-x_i+c_i \quad \text{(xvi)}$$

$$q_i\leq wr_i-p_i-x_i+c_i \quad \text{(xvii)}$$

$$r_t+q_i+x_i-c_i\geq w_i \quad \text{(xviii)}$$

$$q_{K+1}=0 \quad \text{(xix)}$$

Where $\lambda_1,\lambda_2\in[0,1]$

$$x_i, we_i, p_i, q_i, wr_i, c_i, w_i\geq 0 \qquad \forall i\in[k,\ldots.K] \quad \text{(xx)}$$

The fitness function (10) with constraints (11), (12), (13), and (18) minimizes the quantity of irrigation water, constraints (14) and (15) are used to check rainfall efficiency, constraints (16) and (17) are used to check the efficiency of the soil reserve in water (soil moisture), and constraint (19) is used to ensure that at the end of the planting season, the soil reserve is fully used; thus, it is well exploited in order to optimize irrigation water.

To estimate the period and the sufficient amount to irrigate the field, it is necessary to calculate the evapotranspiration of the cultivated areas. For this purpose, the FAO Penman-Monteith method is utilized to estimate the potential evapotranspiration ($P_E$) and the evapotranspiration of the crop ($E_{Tr}$). Equation (21) shows the calculation of the potential evapotranspiration considering the stage of vegetative growth of the crop by weighting the potential evapotranspiration.

$$P_E = \frac{0.408\Delta\left(N_R - S_{hf}\right) + \chi \dfrac{900}{A_t + 273} W_{2m}\left(k_s - k_a\right)}{\Delta + \chi\left(1 + 0.34U_2\right)} \qquad \text{(xxi)}$$

Where $P_E$ denotes the reference evaporation (mm day$^{-1}$), $N_R$ net radiation at the crop surface (MJ m$^{-2}$ day$^{-1}$), $S_{hf}$ is the soil heat flux density (MJ m$^{-2}$ day$^{-1}$), $A_t$ is the air temperature at 2m height ($^0$C), $W_{2m}$ denotes the wind speed at 2 m height [m s$^{-1}$], $k_s$ denotes the saturation vapor pressure (kPa), $k_a$ denotes the actual vapor pressure (kPa), $\Delta$ is the slope vapor pressure curve (kPa $^0$C$^{-1}$) and $\chi$ is the Psychrometric constant (kPa $^0$C$^{-1}$). The calculation of $E_{Tr}$ is the product of $P_E$ and $K_c$, where $K_c$ is determined from the type, growth length of the crop and chooses the corresponding coefficients $K_c$.

$$E_{Tr} = P_E * K_c \qquad \text{(xxii)}$$

Where $K_c$ denotes the single crop coefficient. After fitness evaluation, the population of $n$ beetles is as follows:

$$B = (B_1, B_2, \dots B_n) \qquad \text{(xxiii)}$$

In a $D$-dimensional search space, where the th $i^{th}$ beetle represents a $D$-dimensional vector

$$B_i = (B_{i1}, B_{i2}, \dots B_{iD})^T \qquad \text{(xxiv)}$$

According to the target function, the fitness value of each $i^{th}$ beetle position can be calculated, which is computed via equation (10). The speed of the th beetle is expressed as

$$S_i = (S_{i1}, S_{i2},...S_{iD})^T \quad \text{(xxv)}$$

The individual and group extremity of the beetle is represented as follows:

$$I_i = (I_{i1}, I_{i2},...I_{iD})^T \quad \text{(xxvi)}$$

$$I_g = (I_{g1}, I_{g2},...I_{gD})^T \quad \text{(xxvii)}$$

The mathematical model for simulating its behavior is as follows:

$$B_{id}^{t+1} = B_{id}^t + \kappa B_{id}^t + (1-\kappa)\psi_{id}^t \quad \text{(xviii)}$$

Where $d=1,2,...D; \; i=1,2,...n \; t \; I$; is the current number of iterations. $S_{iD}$ is expressed as the speed of beetles, $\Psi_{iD}$ represents the increase in beetle position movement and $k$ is a positive constant. Then, the speed formula is written as:

$$S_{id}^{t+1} = \omega S_{id}^t + z_1 r_1 \left(I_{id}^t - B_{id}^t\right) + z_2 r_2 \left(It_{gd}^t - B_{gd}^t\right) \quad \text{(xxix)}$$

Where $z_1$ and $z_2$ are two positive constants, $r_1$ and $r_2$ are two random functions in the range [0, 1] and ω denotes the inertia weight. The proposed method uses the inertia weight nonlinear decreasing strategy to achieve the nonlinear decrease with the increase of the number of iterations, that is,

$$\omega = (\omega_{\max} - \omega_{\min})\left(\frac{T_{\max} - t}{T_{\max} - 1}\right)^{\beta} + \omega_{\min} \quad \text{(xxx)}$$

Where $\omega_{\max}$ denotes the maximum value of the inertia weight, $\omega_{\min}$ is the minimum value of the inertia weight, $t$ is the current number of iterations, $T_{\max}$ is the total number of iterations and β is the constant which is ≥ 0. The function β defines the incremental function, which is calculated as follows:

$$\beta_{id}^{t+1} = \sigma^t * S_{id}^t * sign\left(f\left(B_{rd}^t\right) - f\left(B_{rd}^t\right)\right) \quad \text{(xxxi)}$$

Where δ indicates step size. The search behaviors of the right antenna and the left antenna are respectively expressed as:

$$B_{rd}^{t+1} = B_{rd}^{t} + S_{id}^{t} * d/2 \tag{xxxii}$$

$$P_{ls}^{t+1} = P_{ls}^{k} + V_{is}^{k} * d/2 \tag{xxxiii}$$

Based on the evaluated fitness function, the BSO performs the optimization process, and finally, returns the optimal irrigation schedules for the crops for the classified zones of AP.

## 4. Results and Discussion

In this paper, agro-climatic regionalization of AP using HWI-DNN algorithm and optimal irrigation scheduling using BSO algorithm was performed. For this study, the data of all zones of AP was gathered from the records of India Meteorological Department (IMD) and department of Planning, Andhra Pradesh, for a period of 30 years extending from 1988 to 2017. In this section, the results obtained by the proposed methods are compared with the existing techniques regarding some performance measures. Based on the comparative analysis of the techniques, the performance of the techniques is analyzed. The planning aims at scientific management of regional resources to meet the food, fibber, fodder, and fuel wood without adversely affecting the status of natural resources and the environment.

### 4.1 Performance Analysis of HWI-DNN

An analysis of the proposed HWI-DNN algorithm used the graph to better understand the results in comparison with the existing algorithm, such as DNN, ANN, and SVM. Various performance metrics, such as Sensitivity, Specificity, Accuracy, Recall, Precision, F-measure, False Prediction Rate (FPR), the False Rejection Rate (FRR), and False Discovery Rate (FDR) were analyzed. The results were used to understand that the proposed work gave better performance. So, here the performance of the proposed system is plotted against the existing techniques, which are shown in the figures below.

**Figure 2.**
*Performance Analysis of Accuracy, Specificity, and Sensitivity*

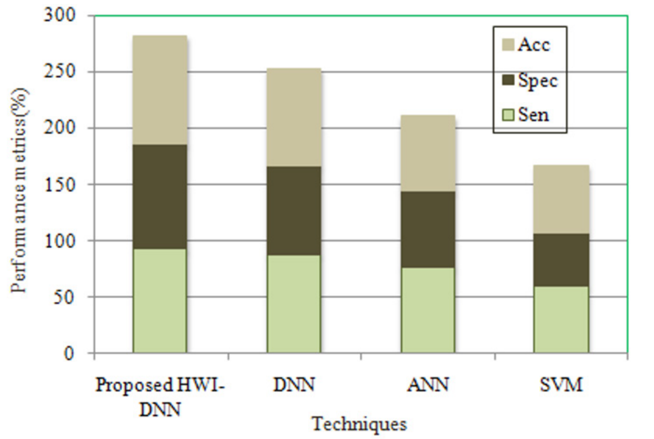



Figure2 shows the best results of the proposed HWI-DNN and other DNN, ANN, and SVM. The sensitivity, specificity, and accuracy of the proposed system are higher than other techniques. The sensitivity of the DNN, ANN, and SVM is 87.53, 76.53, and 59.37.but the proposed HWI-DNN's sensitivity is 92.67. The specificity of the HWI-DNN is 93.16 and DNN, ANN, SVM have 78.26, 67.83, 47.82. Compared with the obtained results, the proposed system has the highest specificity. Similarly, the accuracy of the proposed system is 95.68, which is higher than other DNN, ANN, and SVM.

**Figure 3.**
*Performance Analysis of F-Measure, Recall, and Precision*

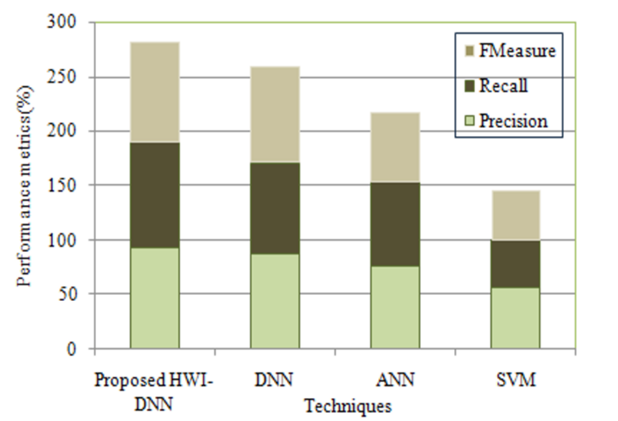


Figure 3 shows the results of precision, recall, and F-measure for classification accuracy. The F-measure of the proposed HWI-DNN is 92.51, and DNN, ANN, and SVM are 87.35, 76.34, and 56.74 respectively. The results' values show that the proposed system has the highest F-measure value than other methods. Then the recall results of the existing DNN, ANN, and SVM have 83.65, 76.52, and 43.57. But the result of the proposed method has 97.56, which is an effective recall. Similarly, the precision value of the proposed method (97.56) is higher than other DNN (83.65), ANN (76.52), and SVM (43.57). These outcomes show that the agroclimatic regionalization using the HWI-DNN algorithm is better.

**Figure 4.**
*Performance Analysis of FDR, FRR, and FPR*

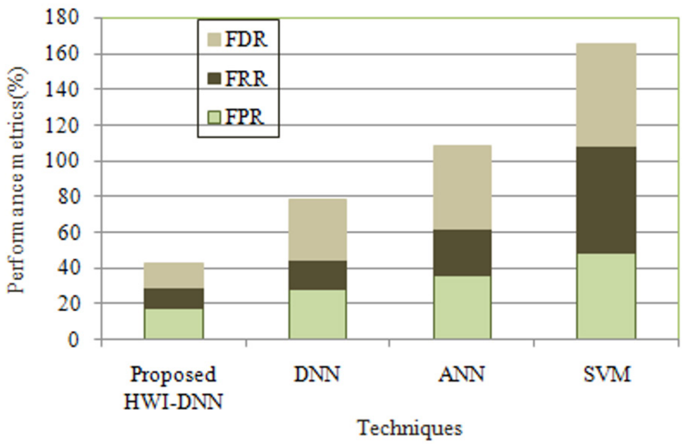



Figure 4 shows the comparison of the classification error detection rate of the proposed HWI-DNN algorithm and the existing algorithm. The False Prediction Rate (FPR) of the proposed method is 17.21 lower than other DNN (27.82), ANN (35.46), and SVM (48.17). Then the False Rejection Rate (FRR) of HWI-DNN is 11.92. When compared with DNN (16.34), ANN (26.78), and SVM (59.83), the proposed system has a lower false FRR. Finally, the False Discovery Rate (FDR) of HWI-DNN is also much lower than other existing algorithms. The consequence of the comparison shows a lower error rate than the existing methods.

**4.2 Performance Analysis of Irrigation Scheduling**

In this section, the optimal irrigation scheduling using the BSO algorithm is analyzed. The study of cereals that were conducted in the Krishna Godavari region in Andhra Pradesh was selected, which included the districts such as East Godavari Part, West Godavari, Krishna, Guntur, and contiguous areas of Khammam, Nalgonda and Prakasam. A variety of sample crops (tobacco) was used. To highlight the necessity of irrigation water optimization andevaluate water use efficiency, the effectiveness or ineffectiveness of rainfall and soil water content were examined. Table 2 below shows the irrigated area of crops in AP.

**Table 2.**

*Crop Wise Irrigated Area in AP for Important Crops*

| Crops | Area under the crops (lakh ha) | Area irrigated (lakh ha) | Percentage |
|---|---|---|---|
| Rice | 21.61 | 20.87 | 96.58 |
| Maize | 2.33 | 1.75 | 75.11 |
| Groundnut | 7.75 | 1.24 | 16 |
| Cotton | 6.66 | 1.04 | 15.62 |
| Other crops | 36.97 | 10.57 | 28.59 |
| Gross area sown | 75.32 | 35.47 | 47.09 |

**Table 3.**

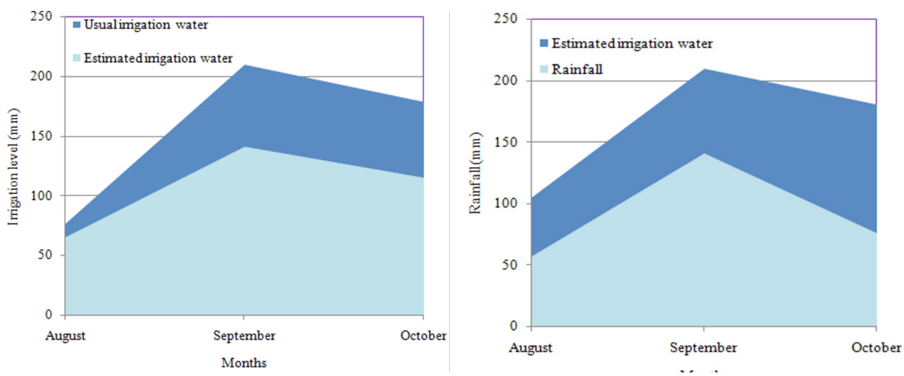
*Summary of Monthly Results during the Development ycle (August- October)*

| Months | August | September | October |
|---|---|---|---|
| Rooting depth (cm) | 13-18 | 19-22.5 | 23-36 |
| (mm) | 43.86 | 56.98 | 73.89 |
| (mm) | 26.6 | 13.9 | 15.8 |
| (mm) | 22.78 | 28.89 | 37.91 |
| (mm) | 46.76 | 47.98 | 34.23 |
| (mm) | 65.56 | 83.67 | 108.52 |
| (mm/month) | 43.5 | 47.90 | 92.24 |

Results in Table 3 illustrate the monthly variables over the experimental study field that was used to resolve the optimization problem. The planting period varies from one plant to another and can be measured with any usual temporal unit, in which **"*t*"** is the planting time and "***T***" is the harvest time. $N_w$ is needed water, and it refers to the water lost through evapotranspiration, which is month1 43.5mm, month 2 47.90mm, and month 3 92.24mm. The $N_w$ varies from one plant to another. $r$ is efficient rain, $WR_{max}$ is maximal useful water reserve, which increases as per crop growth. EUR is an easily used water reserve. $s$ is soil moisture, which varies from place to place, and $I$ is irrigation water, $c$ is drainage water. These values are the decision variables of the linear optimization model. [59, 60]

**Figure 5.**

*(a) Usual and Estimated Irrigation Water from August to October (mm) (b) Relation between Estimated Irrigation and Rainfall.*




**(a)** **(b)**

Figure 5(a) shows the monthly difference of estimated and usual irrigation water from August to October. There has been a positive difference between the usual and estimated irrigation water. This difference increases to reach the highest value in September, which is usual irrigation at 210 mm, and then decreases to 178.75 mm until October. But in estimated irrigation, the highest value in September is 140.66mm, which then decreases to 114.67mm in October. Moreover, by looking at Figure 5 (b), it can be noted that there is a direct proportion between rainfall and the difference between the losses due to the evapo-transpiration and drainage on the one hand, and the estimated irrigation water on the other, which means that there is a decrease in the amount of irrigation water accompanied with an increase in rainfall, which proves that there is an optimized use of rainwater as an alternative resource for irrigation. This is one of the most important features of the proposed model.

## 5. Conclusion

This paper proposed a deep learning algorithm, namely IHW-DNN for performing agro-climatic classification of AP. In addition, a novel fitness function based BSO was also proposed for performing irrigation scheduling of the classified zones of AP. The performance analysis of the proposed methods was compared with the existing algorithms in terms of some performance metrics. The result of the proposed IHW-DNN obtained the highest value of sensitivity, specificity, precision, recall, f-measure, and accuracy and the lowest value of error rate metrics when compared to the existing algorithms. Likewise, the results of the proposed irrigation scheduling mechanism were compared with the usual irrigation scheduling mechanism. The scheduling obtained by the proposed BSO gave the optimal irrigation of crops in the classified zones. This paper focused on the classification of zones with well-known and dynamic data of rain fall and temperature. In the future, the work can be extended by including advanced methods for performing classification of climate change in AP zones based on some field parameters of AP with the feature selection algorithm with the aim of reducing the training time of the classifier. In addition, a crop cultivation system shall be proposed for the classified climatic zones of AP with optimal irrigation scheduling strategy.

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