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Moths-Flame Optimization Algorithm for Spatial Prediction of Wildfire Probability

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Abstract: In terrestrial ecosystems, the increased frequency and intensity of wildfires are often caused through the weather change and human negligence. In this manuscript, the validation of spatial prediction of wildfire probability based on Moths-flame optimization algorithm is proposed. To evaluate optimization algorithm for wildfire modeling, in moth-flame optimization algorithm are analyzed by a data as fire-prone landscape at Hyrcanian eco region of north Iran. Here, the relative changes of the stepwise weight assessment ratio analysis (SWARA) weights at every class of the variable indicate the predictive value in various stages of spatial correlation among the predictor variable in fire events. At last, the proposed algorithm is executed in MATLAB site. The experimental outcome portrays that proposed system performs better depending on specificity, sensitivity, accuracy, false alarm ratio (FAR), root mean square error (RMSE), Kappa. The proposed SPWP-WFO provides higher performance for accuracy in 3.15%,2.08% and 5.37%, sensitivity is 6.59%, 6.59% and 3.19%, specificity is 6.52%, 5.37% and 7.69%, RMSE value is 61.11%, 81.25% and 45% and kappa value is 5.31%, 2.06% and 5.31% compared to existing algorithms such as Genetic algorithm (GA), Particle swarm optimization (PSO), Shuffled frog leaping algorithm (SFLA).

Keywords: *Wildfire prediction, moth flame optimization, genetic algorithm, step wise weight assessment ratio.*

1. INTRODUCTION

The wildfires play a major role in natural disasters. Wildfires treat as the ecosystem that has affected the life of human and probability and ecological procedures with operations [1, 2]. In the past periods, significant universal augments in count and harshness of wildfire are reported [3]. When the feasibility of wildfire occurrence is spread and strongly affected by various methods are grouped as 4 major classes they are, (i) climate, (ii) vegetation, (iii) topography and (iv) human behavior [4, 5]. When human affect the frequency and spatial pattern of fire by providing the natural vegetation and source of altering the limit of fire [6]. In several studies spatial wildfire forecasting possibility utilizing GIS and RS are activated in various methods like fuzzy logic, analytical network process [7]. Natural risk is difficult operation along multi-spatial and temporal drivers in hybrid modeling have increased due to the enhanced predictive accuracy of the natural occurrences [8, 9]. In hybrid model several combination of the adaptive neuro-fuzzy inference system (ANFIS) integrated to meta-heuristic optimization approach and the distinction of development has utilized to upgrade the natural hazard forecasting via, landslide, flood [10].

In this manuscript, the meta-heuristic optimization algorithm has attained fairly good result in various mapping studies in natural hazard susceptibility [11, 12]. Some common metaheuristic optimization algorithms are employed in broad range of investigations in wildfire field like artificial intelligence based on neuro fuzzy system. In spatial prediction of wildfire probability with moth flame optimization algorithm is proficient for wildfire forecasting than the earlier preferred method such as GA and PSO algorithm. The advantages of the SPWP in MFO are significantly to reduce the uncertainties in wildfire modeling mainly optimized the MFO algorithm. This approach requires the weight parameter determination.

The main contribution of this manuscript are summarized as below,

- In this manuscript, the spatial prediction of wildfire probability based on moth flame optimization (MFO) approach is implemented.
- MFO approach is analyzed utilizing a data from fire-prone terrain at Hyrcanian eco region of north Iran.
- A spatial dataset is build depending on 159 fire cases from Hyrcanian eco region, where a set of predictor variables.
- The SWARA method is utilized to allocate weights to each predictor variable class.
- The methods are verified by some performance metrics and likened with SPWP method. When the SPWP model excels the hybrid methods on training phase, their accuracy is significantly lower on the validation phase.
- The experimental outcome portrays that moth-flame optimization algorithm is more competent to deal the over-fitting issue of SPWP method in the learning process of fire model.

The rest of this manuscript is mentioned as: Section 2 delineates that literature survey. Segment 3 describes the proposed method. Segment 4 demonstrates the experimental result and discussion. Finally, Segment 5 concludes the manuscript.

2. LITERATURE REVIEW

Certain recent literatures related to spatial prediction of wildfire probability through various approaches which are explained as follows,

In 2018, *Nami et al* [13] have presented a wildfire management and risk assessment for accurate estimate of wildfire probability and production of distribution map. Here, northern Iran, Hyrcanian Eco region was the part of wildfire probability was to predict the spatial pattern in the geographical information system (GIS) and the technique was incorporated automatically with the quantitative data driven evidential belief operation. The experiment results show the probability map exposed with maximal probability involved almost 60% of the terrain.

In 2019, *Joseph et al* [14] have presented the spatio temporal forecast of wildfire size extremes along Bayesian finite sample maxima for predicting the extreme wildfire across the United States. Here, they compared different distributions in the large fires to generate the finite sample maximum for extreme phenomenon based on the posterior predictive distribution. The presented model attains the interval coverage was 99% in the count of fires and 93% in fire size over 6 years dataset. Then the recent excesses cannot be unexpected that the attached United States on edge of the even larger wildfire extremes.

In 2019, *Hong et al* [15] have presented the effect of common landscape stage displays on wildfire as well as spatial weakness diagonally the fire-prone landscape at southeast China. The presented method incorporates the Weights-of-Evidence (WOE) and Analytical Hierarchy Process (AHP). The proficiency of the presented method was likened to logistic regression including single WOE method, then comparative analysis utilizing Wilcoxon signed-rank tests established a noteworthy development of wildfire forecast with the help of incorporated WOE-AHP method than the other methods.

In 2017, *Jaafari et al* [16] have suggested the WOE was employed by Bayesian modeling to examine the spatial association among the historic fire cases in Chaharmahal-Bakhtiari Area, Iran. The binary predictor variable was used a wild range of topography, climate, and human activities. The validation result shows that the area under the curve for the predictor model includes geography 84.6, weather 80.4%. The highest AUC for the rate of achievement was 86.8%, prediction was 84.6% attained by the analysis.

In 2019, *Khakzad et al* [17] have presented the dynamic Bayesian network for modeling wildfire spread in the interfaces of wild land and industrial. Here, the wildfires risk was the security and reliability of industrial plants, then activate the secondary fires and explosion especially at process plants case by the huge list of explosive and combustible material was present. The modeling of WII as 2D lattices, a new method was developed for WII combining the wildfire speed and assessing the risk in the Bayesian network.

In 2017, *Cao et al* [18] have presented the wildfire exposure and its main influencing factors were vital area wildfire risk management. Here, the wildfire weakness estimation was performed through multi models, such as logistic, probit regression, artificial neural network, random forest (RF) approach. The experimental results demonstrate that the cost sensitive RF and the accuracy was high for all samples in 88.4% and 94.23% accuracy in explosion prediction. Vulnerability map developed by the spatial variations that provides the information regarding to vulnerability, which was employed in regional wildfire risk management.

In 2019, *Jaafari et al* [19] have presented an intelligence hybrid model that depends on ANFIS and the grey wolf optimizer (GWO) including biogeography-based optimization (BBO) approach, which was gaining the landslide susceptibility. The ANFIS model was developed by initial landslide susceptibility model optimized by GWO and BBO algorithms. Those models were verified by large number of runs in training, validation datasets. The presented model established an enhanced prediction of landslides likened to existing studies along different models. Consequently the new model was presented for landslide modeling vulnerability and the modelers could simply tailor based on its individual conditions.

In 2019, *Tehrany et al* [20] have presented dependable forest fire vulnerability map requires for destruction management along primary reference source in land utilize scheduling. Here, a fire list database for the investigate region was build depending on the existing forest fire occurrence data and number of generated sources that related to condition factors. The performance was compared to area in terms of curve, kappa index, sensitivity, specificity, accuracy, positive and negative forecast value. The experimental outcome portrays that training and validation dataset representing 92% prediction capability.

3. PROPOSED METHOD FOR SPATIAL PREDICTION OF WILDFIRE PROBABILITY USING MOTHS-FLAME OPTIMIZATION ALGORITHM

In this section, a moth-flame optimization approach [21] for proposed algorithm is discussed. The main source is to arranging the list in historical fires by natural resources in Golestan Area. In wildfire model, the spatial relationship among historical fire phenomenon by the predictor variable is investigation of data correlation analysis. After discrete, the predictor variable is divided as classes, the weight of class signifies the fire event intensity by the correlation analysis. In this manuscript, the SWARA method is used to measure the weight, this is an innovative multi-criteria decision making (MCDM) method. This work assumes that the relative changes of step-wise weight assessment ratio analysis in every class of the variable indicate the predictor value at the various stages of spatial relation amid the predictor variable and fire event. Earlier MCDM technique are used to analytic hierarchy process (AHP) as well as analytic network process (ANP), which generate that hierarchical model utilized for training of forecast variables. In this method, a 70/30 ratio is employed to create training with validation datasets. The training dataset is to create fuzzy inference system with adaptive fuzzy inference system. Then, the parameter is to optimize the moth flame optimization approach that can be created by the spatial prediction of wildfire probability in moth flame optimization approach. The objective function of the moth flame optimization strategy determines that error magnitude in the prediction variable of root mean square error.

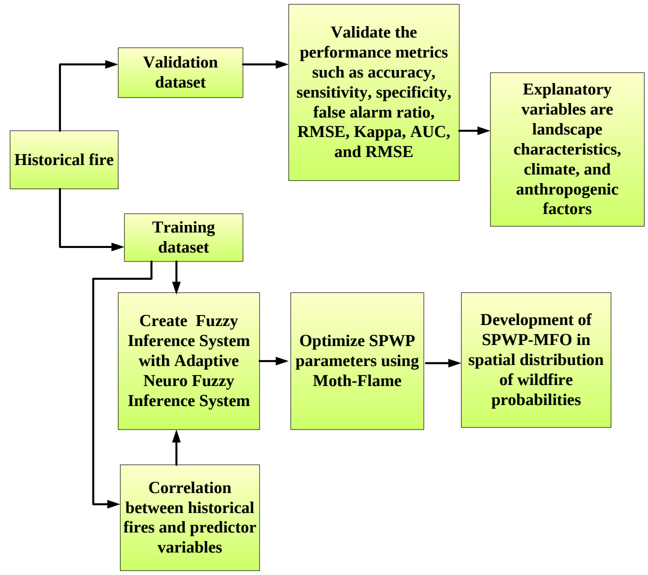

Figure 1: Block diagram for proposed algorithm

In validation dataset, the validation of performance metrics such as, FAR, RMSE, specificity, accuracy, Kappa, sensitivity, AUC are presented. In ROC terms, the training data set returns the proficiency rate of method. To develop the integrated susceptibility model, the land scale indicates weight of evidence in AHP to perform and analysis the each indicator in final weight. Prediction of wildfire probability based moth flame optimization algorithm was analyzed and compared with existing algorithm like GA [22], PSO [23] and SFLA [24].

In this method, the integrated models are calculated in indicator rating is computed for the landscape indicator using spatial association along the historical fire location are calculated,

$$I = | RX_{\max} - RX_{\min} | / RX_{\max} | - RX_{\min} |_{\min} \tag{1}$$

Where $RX_{\max} | - RX_{\min} |_{\min}$ Are the absolute difference in the lowest indicators.

Here, the fire occurrence and the predictive performance are compared depending on test set at posterior prognostic check for zero proportion, maximal count and overall count. The methods are vary based on negative binomial random variable and representing the counts of a poison. In poison distribution is a count for the common choice that provides the binomial distribution. The zero overstated versions the component that represents the extra zeros and include the distributions, which has predictable to autonomous process whether to determine the possible non-zero counts

In spatial units of eco region $r = 1, \ldots, R$ and time represented as $t = 1, \ldots, T$ and the probability mass function is defined in each term for $m_{r,t}$. The fire over the eco region is r and time t. Each distribution is in the consideration in local parameters that has $\mu_{r,t}$ that allowed to vary in time and space. To ensure that log link function we can use that $\mu_{r,t} > 0$ and $\pi_{r,t} \in (0,1)$. Concatenating over Spatial with temporal unit we can use, $\mu = (\mu_{r=1,t=1}, \mu_{s=2,t=2}, \ldots\ldots, \mu_{r=R,t=T})$ similarly the modeling position π and related zero inflation parameters are calculated as given equation ()

$$\log(\mu) = \alpha^{(\mu)} + Y\beta^{(\mu)} + \phi^{(\mu)} + \log(b) \qquad (2)$$

$$\log(\pi) = \alpha^{(\pi)} + Y\beta^{(\pi)} + \phi^{(\pi)} \qquad (3)$$

Where, $\alpha^{(\mu)}$ and $\alpha^{(\pi)}$ represents scalar intercept parameters then Y denotes $(R \times T) \times q$ in the design matrix, here q represents the count of input features $\beta^{(\mu)}$ and $\beta^{(\pi)}$ represents the length q in the column vector parameter, $\phi^{(\mu)}$ and $\phi^{(\pi)}$ represents the length of $(R \times T)$ in column vector parameter that containing spatiotemporal changes. Then b is a offset vector area for the spatial units $r = 1,2,\ldots.,R,$ that has repeated in T times. The step by step procedure for Moths-flame optimization algorithm of SPWP are given below

3.1 Step by step procedure for Moths-flame optimization algorithm for SPWP

In this section, the spatial perdition of wildfire probability in moth-flame optimization approach is discussed. MFO is a nature stimulated algorithm is easy to execute. The MFO algorithm is straight forward to develop the procedure in spatial prediction of wildfire probability (SPWP). The first step of the MFO algorithm is to generate the solution space with moths are randomly neighborhood within the spatial prediction of wildfire probability. And then fitness value for each moth is calculated by the tagged flame and obtained the best position. Updating the spatial prediction, the end process is attained until the probability of the spatial prediction of wildfire probability for Moths-flame optimization algorithm (SPWP-MFO). MFO algorithm starts with the random population, each individual of population is called flame. The performance of SPWP model, set of parameter value is for optimal combination is to optimize the MFO. In spatial prediction of wildfire probability in moth-flame optimization algorithm consists of following stages they are, initialization, random generation, fitness function, optimal global solution, exponential term, flame number, performance evaluation and validation procedures are given below.

Step 1: Initialization

Initialize the initial population P using SPWP-WFO. Then the initialization of the spatial prediction of wildfire probability equation is,

$$P = \begin{Bmatrix} p_{1,1} & P_{1,2} & \cdots & P_{1,n} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,f} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n,1} & P_{n,2} & \cdots & P_{n,f} \end{Bmatrix} \qquad (4)$$

Where n denotes that number of moths on search space, f represent the dimension variable.

Step 2: Random generation

After the initialization process the initial constructions are depends on number of particles and dimensions with random initialization are as follows,

$$RP = \begin{Bmatrix} RP_{1,1} \\ RP_{2,1} \\ \cdots \\ RP_{n,1} \end{Bmatrix} \qquad (5)$$

Here, RP represents the random initialization of the fitness function.

Step 3: Fitness function

In this step, the spatial prediction of wildfire probability in moth flame optimization uses the optimization process to start the initial population. This is vital to fit the dimension is equal moth as well as flame for equal fitness value that is represented as,

$$RE = \begin{Bmatrix} RE_{1,1} \\ RE_{2,1} \\ \cdots \\ RE_{n,1} \end{Bmatrix} \qquad (6)$$

In moth flame optimization the solution to a problem can be obtained by the path for planning the moth and flame resolution. Then the elements are evaluated by the fitness function that is determined in step 4. Then overall flow chart of proposed SPWP-WFO algorithm is delineated in Figure 2.

Step 4: Optimal global solution

In this step, optimal global solution is discussed. The moth flame optimization algorithm is measured as a competent three-tuple algorithm at optimization issue. Then the mathematical formulation is given at equation (7)

$$M = (J, E, L,) \qquad (7)$$

Where, J denotes ability to arbitrary create value in the population by searching neighborhood and the equal fitness value. Then, E represents the mathematical formulation of key function representing the movement of moth during the search around the neighborhood space, and L represents the useful function which checks the acceptable level of the system.

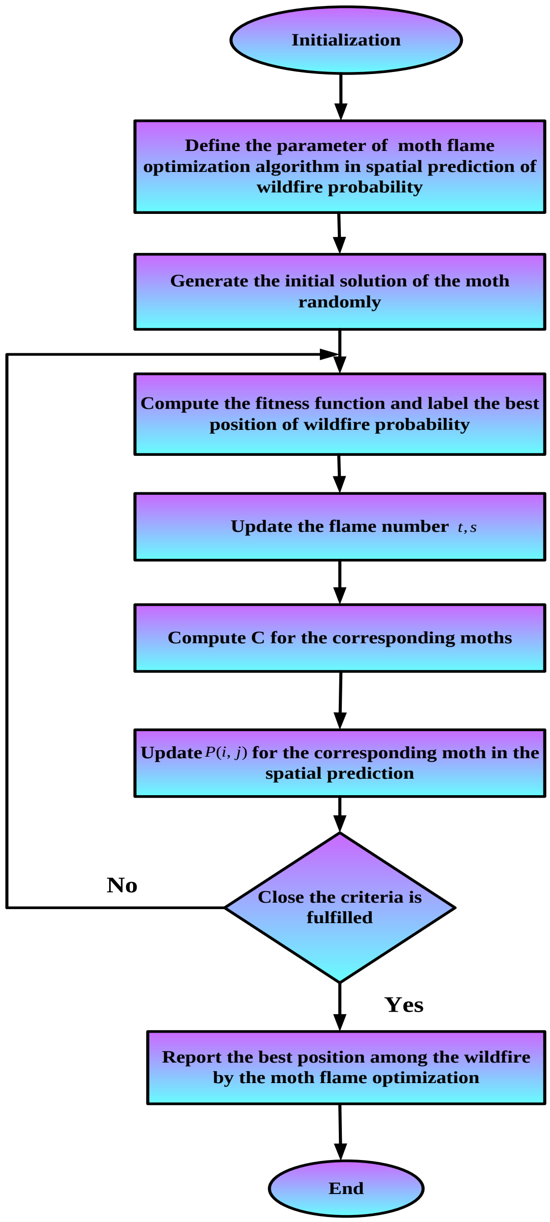

Figure 2: Flow chart for spatial perdition of wildfire probability in moth-flame optimization algorithm

Step 5: Exponential term

In the updating rule, the main concentration of the next contribution is the exponential term and the general framework exploited in term $J, E, L,$. Then the variable equally has the upper and lower bond and the variable arrays are shown in symbol ub and lb are calculated in equation (8) and (9)

$$ub = [ub_1, ub_2 \ldots ub_{n-1}, ub_n] \quad (8)$$

$$lb = [lb_1, lb_2 \ldots lb_{n-1}, lb_n] \quad (9)$$

The function E, L and J referring the initialization process and the key function E is replicated iteratively until the function L. The function E remainders the absolute function that enables the moth's movement from one place to another. Every moth position is updated using flame, which is expressed as,

$$P_i = R(P_i, E_j) \quad (10)$$

Where, R denotes the spiral function, P_i denotes i-th position in moth, whereas j describes j-th flame. In spiral function contain certain condition with attention on the position of moth including flame at space, the systematic representation in spiral operation of MFO is described as,

$$R(P_i, E_j) = C_i . F^a . \cos(2\pi t) + E_j \quad (11)$$

Here, C_i denotes that feasible distance planned to i-th moth to j-th flame on structure and a denotes the constant which defines the logarithmic spiral shape in the system.

Step 6: Flame number

In this step flame number has to discussed and the equation describing the flame number (E_N) is given in equation (12)

$$E_N = r[(N - J) * (N - 1/T)] \quad (12)$$

Here, E_N represents that flame number, T denotes the maximal number of repetition is possible, J represents that iteration position.

Step 7: Performance evaluation

In this step the performance evaluation of the spatial perdition of wildfire probability in moth-flame optimization algorithm discussed. The SWARA mode is used for assigning weights for every class of every predictor variable is presented with comparative study of result and the consultants.

Step 8: Validation

In this step, the importance and throughput of moth flame optimization technique are validated based on proposed methodology. In ROC term wildfire probability, the success rate of training model indicates how relevant the method result. The validation phase ROC produces that forecast rate and calculates how the method forecasts the typical probability of the fire events. Then, the performance of the SPWP-MFO is validated contradiction of the existing algorithm like GA, PSO and SFLA algorithms.

4. RESULT AND DISCUSSION

Here, the simulation performance of proposed spatial prediction of wildfire probability based on MFO approach is discussed. The simulation is executed in MATLAB site on PC along 3.30 GHz Intel(R) Core(TM) i5CPU, RAM 6 GB, MS Windows 8.1 operating system [25]. This work assumes that the relative changes of SWARA weights on every class of the variable indicate the predictor value at various levels of spatial correlation amid the predictor variable and fire events. Here, the performance of the proposed spatial method; prediction of wildfire probability based moth flame optimization algorithm was analyzed and compared with existing algorithm like GA, PSO, SFLA. Table 1 tabulates the simulation parameters of proposed algorithm.

Table 1: Simulation parameter

Parameter	Value
Software	MATLAB
Count of iteration	1000
Population	100
area covers approximately	1531 km2
study area	East Hyrcanian eco region of north Iran

4.1 Simulation result of the proposed spatial prediction of wildfire probability using moth flame optimization algorithm

Figure 3 shows that the implementation of spatial prediction of wildfire probability using moth flame optimization algorithm. The values are classified using normal interruptions when the probability of wildfires is generated as every pixel value of landscape research. In prediction of wildfire probability, there are five spreading maps low, very low, high, very high, moderate. Examine the credibility of these maps and likened with five probability maps in the density of fire.

The probability map is properly organized in the values of fire density values augments from very low to very high wildfire levels are detected and predicted by the correlated value. When increasing the fire density with the predicted probability that means the true wildfire possibility. The experimental outcome shows that the five probability maps of wildfire probability using moth flame optimization algorithm. When the comparison of the wildfire possibility levels represents the comparative position of the wildfire probability incidence depends upon the modeling approach. For example high including very high zones are wildfire probability occurrence covers the value at high is 1.1, -1.5, very high zone value is 1.5, -4.6, and historical fire are located within low and very low zone then the low zone value is -0.28, -0.46, very low zone value is -2.7, -0.28 and moderate value is 0.46, -1.1 respectively.

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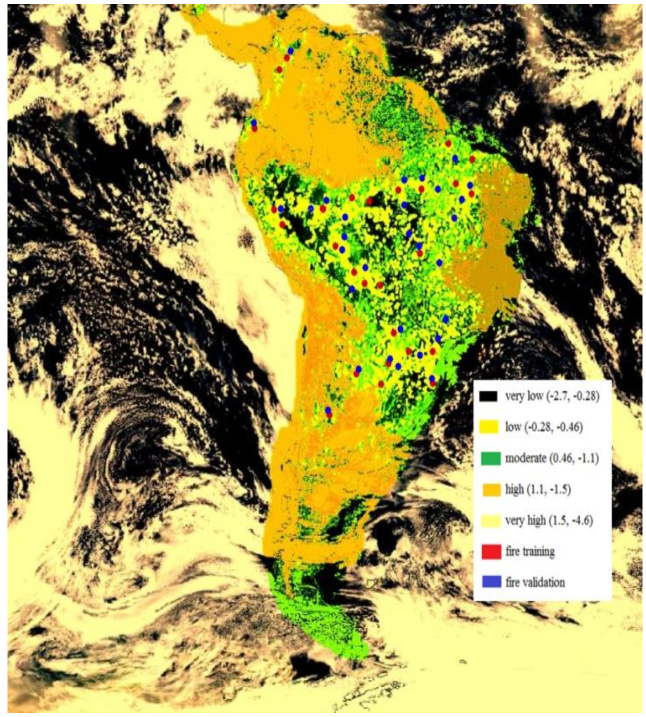

Figure 3: Simulation result of the proposed spatial prediction of wildfire probability using moth flame optimization algorithm

4.2 Performance comparison of training validation dataset

Figures 4 to 11 portrays the simulation outcomes. In this segment, the various performance metrics such as, FAR, RMSE, sensitivity, accuracy, specificity, Kappa are discussed. Here, the performance of the proposed spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) was analyzed and compared to GA, PSO, and SFLA by varying the number of values.

Figure 4 depicts the performance metrics of accuracy in training with validation dataset. In training dataset, the accuracy of the proposed model spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 3.09% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 4.16% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 2.04% higher than SPWP using SFLA. At validation dataset, an accuracy of the proposed method spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 3.15% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 4.16% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 2.04% higher than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA).

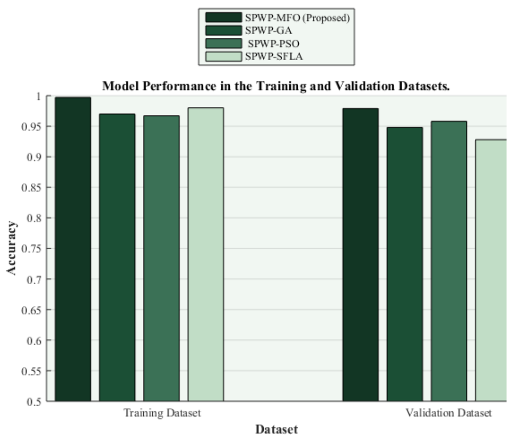

Figure 4: Accuracy analysis

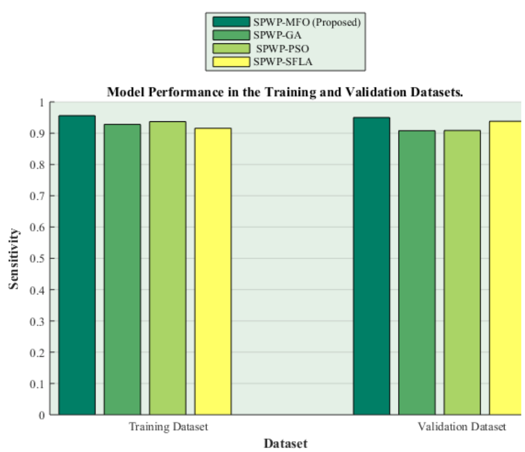

Figure 5: Sensitivity analysis

Figure 5 shows that the performance metrics of sensitivity in training with validation dataset. In training dataset, the sensitivity of the proposed method spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 2.08% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 1.03% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 6.52% higher than SPWP using SFLA. At validation dataset, sensitivity of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 6.59% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 6.59% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 3.19% higher than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA).

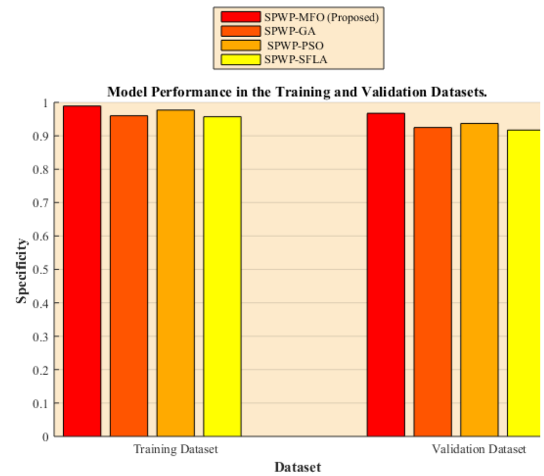

Figure 6: Specificity analysis

Figure 6 portrays that performance metrics of specificity on training with validation dataset. In training dataset, the specificity of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 2.06% higher than existing spatial prediction of wildfire probability with Genetic algorithm (GA), 1.02% higher than spatial prediction of wildfire probability with Particle swarm optimization (PSO) and 3.12% higher than SPWP using SFLA. At validation dataset the specificity of proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 6.52% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 5.37% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 7.69% higher than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA).

Figure 7 shows that the performance metrics of false alarm ratio in training and validation dataset. In training dataset the false alarm ratio of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 87.5% lower than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 66.6% lower than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 83.3% lower than spatial prediction of wildfire probability using SFLA. In validation dataset, the false alarm ratio of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 55.5% lower than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 46.66% lower than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 57.3% lower than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA).

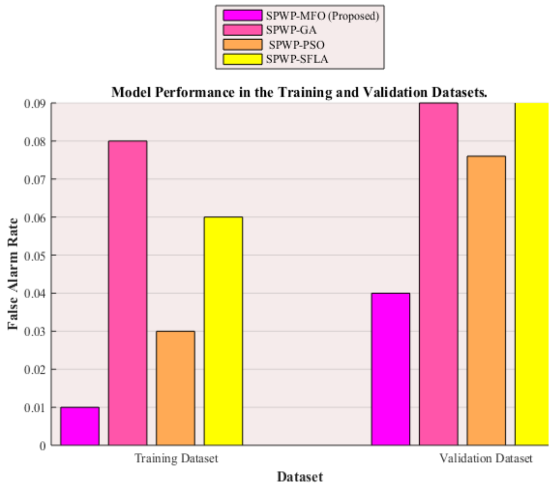

Figure 7: False alarm ratio analysis

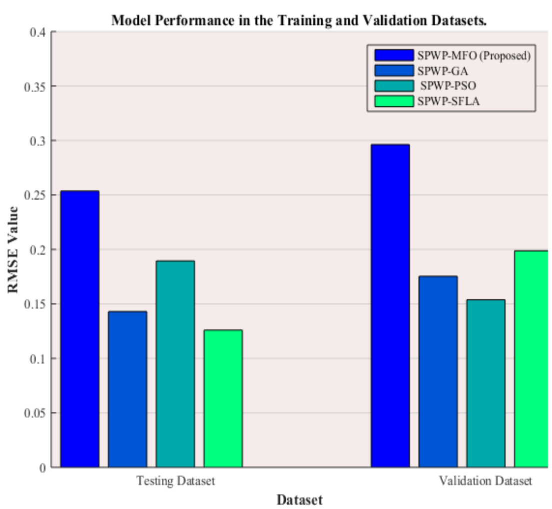

Figure 8: Root mean square error analysis

Figure 8 shows that the performance metrics of RMSE in training with validation dataset. In training dataset, the RMSE of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 85.71% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 44.44% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 13.6% higher than SPWP using SFLA. At validation dataset the RMSE of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 81.25% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 61.11% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 45% higher than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA).

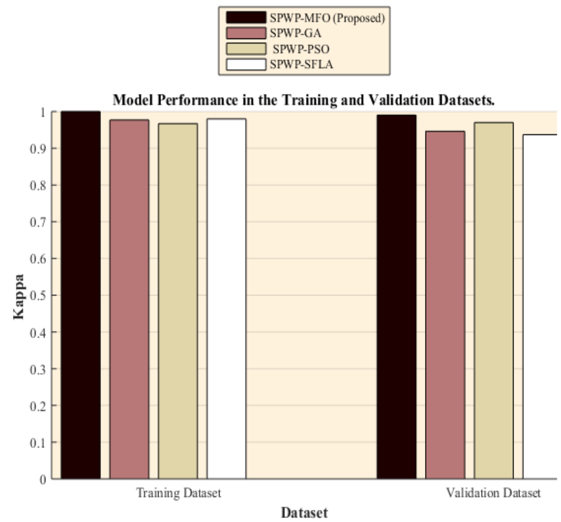

Figure 9: Performance metrics of kappa analysis

Figure 9 shows that the performance metrics of kappa in training with validation dataset. In training dataset, the kappa of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 2.04% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 3.09% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 2.04% higher than spatial prediction of wildfire probability using SFLA. In validation dataset, the kappa of the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 5.31% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 2.06% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 5.31% higher than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA) respectively.

Figure 10 shows that the comparison analysis in training dataset is discussed. In training dataset, the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 0.302% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 0.201% higher than spatial prediction of wildfire probability using

Particle swarm optimization (PSO) and 0.101% higher than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA) respectively

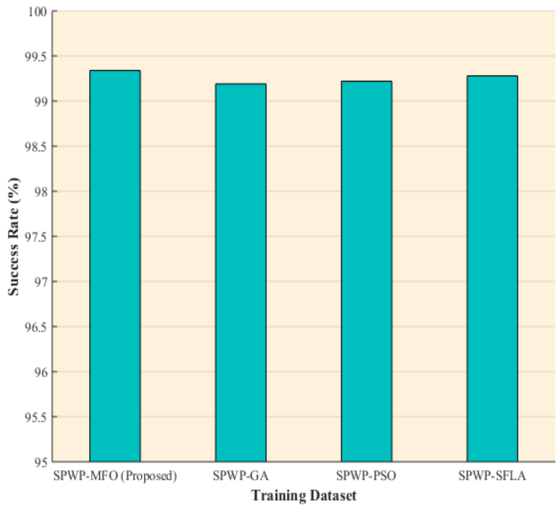

Figure 10: Success rate of training dataset

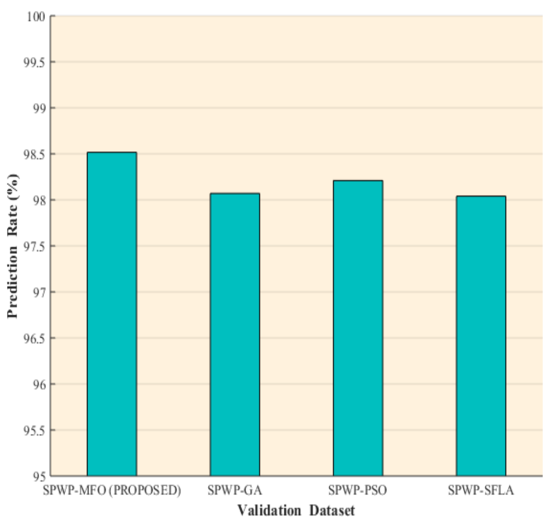

Figure 11: Prediction rate of validation dataset

Figure 11 shows that the comparison analysis in validation dataset is discussed. In validation dataset, the proposed method in spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) produce 0.407% higher than existing spatial prediction of wildfire probability using Genetic algorithm (GA), 0.305% higher than spatial prediction of wildfire probability using Particle swarm optimization (PSO) and 0.51% higher than spatial prediction of wildfire probability using Shuffled frog leaping algorithm (SFLA) respectively.

6. CONCLUSION

In this manuscript, a spatial prediction of wildfire probability using moth flame optimization algorithm (SPWP-MFO) is proposed. Here, the values are classified depending on normal disruptions when the SPWP generation of every pixel value of landscape studies. In prediction of wildfire probability, there are five spreading maps, very low, low, moderate, high, very high. For examining the credibility of these maps and likened with the five probability maps in the fire density. The experimental outcomes demonstrate the performance for training dataset that provides higher performance on the accuracy is 3.09%, 4.16% and 2.04%, sensitivity is 2.08%, 1.03% and 6.52%, specificity is 2.06%, 1.02% and 3.12%, RMSE value is 85.71%, 44.44% and 13.6% and kappa value is 2.04%, 3.09% and 2.04% and lower performance on false alarm ratio 87.5%, 66.6% and 3.12% compared with existing algorithms like GA, PSO and SFLA respectively.

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