CHAPTER 6
IDENTIFICATION OF SUITABLE MAR SITES, MAR RATE AND SCHEDULE

6.1. MAR Site Selection

Selection of the optimal sites for MAR is the fourth step in the proposed MAR framework. The selection of appropriate recharge sites is crucial, as it influences the recharge technique and success of the applied intervention (Sallwey et al. 2019). Geographical Information System (GIS) based Multi Criteria Decision Analysis (MCDA) has been a prevalent method in identification of potential recharge sites based on the surface and aquifer characteristics (Sallwey et al. 2019). Their advantage lies in the readily available remote sensing data of large and inaccessible locations that can be used for preparing thematic maps. However, there was no standard methods to select important factors or to assign them suitable weights (Alkhatib et al. 2021). Other methods of site selection involved application of numerical and analytical techniques (Alkhatib et al. 2021), or use of numerical models in tandem with GIS-MCDA techniques to assess the impact of potential MAR structure placement (Russo et al. 2015; Sashikkumar et al. 2017) or to compare potential recharge zones (Jasrotia et al. 2019). But the studies lacked the consideration of aquifer response to MAR. Khalil et al. (2022) felt that the best sites for MAR were those where large quantity of water could be recharged without altering the groundwater flow or causing excessive rise in head.

Assessment of aquifer response to MAR is usually based on the changes in groundwater levels below the recharge structure (Alkhatib et al. 2021). Bower (2002) states that aquifers should be adequately transmissive to avoid excess build-up of groundwater mound. The height of the groundwater mound created, indicates the total response of the aquifer and its hydraulic properties to MAR. Alkhatib et al. (2021) further stated that the mounding height was directly proportional to the volume of water infiltrated and inversely proportional to aquifer transmissivity, provided other aquifer properties and the MAR design was fixed. Initially, the mound height was determined using analytical techniques (Hantush 1967) based on many simplifications. Numerical models allowed for a more realistic representation of the field conditions and were found to be computationally elaborate (Ringleb et al. 2016). Additionally, in case of the most widely used distributed groundwater flow models, it would be impossible to assess the MAR response at each grid cells to identify potential recharge sites.

In this thesis, an innovative approach is presented to classify the study area into cluster, based on their similar surface and aquifer hydrologic properties, using K-means clustering technique. The outcome of this study would be beneficial to understand the application of clustering techniques to reduce computational time in assessing aquifer response to MAR using regional groundwater flow models. Overall, it would provide a basis with which one can evaluate the potential of any area as an effective MAR site without actually constructing anything on field and consequently saving stakeholders valuable time and money. The work also encourages the use of remote sensing data, mathematics based dimensional reduction techniques, and numerical models in water resource management.

6.1.1. Methodology

The present study has been conducted in four different phases (**Figure 6.1**). The first phase involved preparation of all requisite resource maps using remote sensing and SRTM-DEM data into thematic maps using GIS environment. Aquifer parameter thematic layers were prepared from interpolated maps of pumping test data from exploratory wells (CGWB 2017). In the second phase, Analytic Hierarchy Process (AHP) was employed to refine 10 of the most commonly adopted surface and sub-surface parameters for MAR (Sallwey et al. 2019) to seven. It was done to reduce the computational time in the next phase. The third phase involved application of classical K-mean clustering technique to distribute the study area into small clusters of similar hydrologic properties. In the final phase, MODFLOW-NWT was employed to evaluate the aquifer response at the centroid of each cluster.

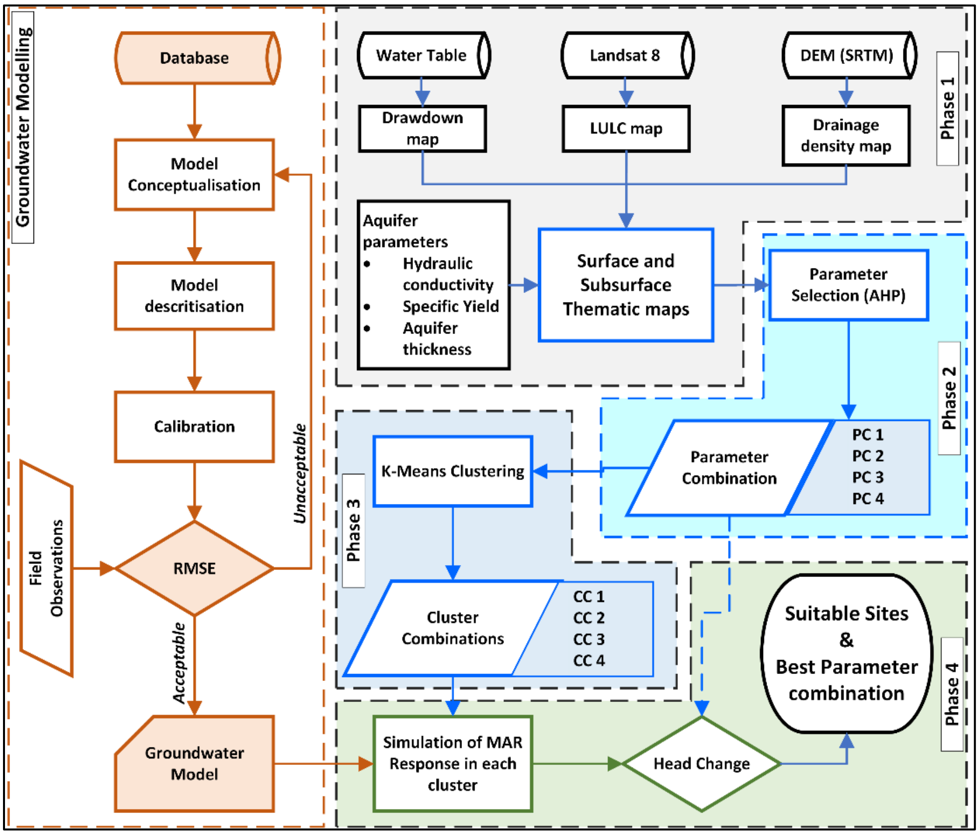

Figure 6.1 Methodology flowchart for Cluster Analysis

6.1.1.1. AHP Technique

Analytic Hierarchy Process (AHP) is a multi-criteria assessment model widely used for handling complex decision-making processes, also applied in area of water resources and MAR site selection process (Gdoura et al. 2015; Jozaghi et al. 2018). In the present study, AHP was employed to determine the 7 most sensitive parameters to MAR site selection from 10 most commonly used ones (Sallwey et al. 2019). First, the structural hierarchy of surface and aquifer hydrologic properties were assembled at different levels.

The pairwise comparisons of attributes with respect to the goal using the relative scale measurements were done in the later step to calculate the weights of various criteria. In the next step, the comparisons were transformed into weights to analyse the properties on a numerical scale. The weightage of the properties was assigned based on reported literature (Ahmad & Verma 2018; Tarigan et al 2018) and expert advice. Finally, the priority vectors and consistency ratio were calculated and presented (**Table 6.1**). The Consistency Ratio (CR) was calculated to check the uniformity of the dataset using the formula:

$$\mathrm{CI} = \frac{(\lambda_{\mathrm{max}} - \mathrm{n})}{(\mathrm{n}-1)} \tag{6.1}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{6.2}$$

Where, λ_{max}= the largest eigenvalue of the comparison matrix, n = the number of responses, CI = the consistency index, and RI = random index for the size of matrix. The principal eigen value was 12.3 and the consistency ratio was found to be 8.6% which was less than 10% hence acceptable (Saaty 1980). The sensitivity analysis to detect how the change in the weight alters the results was also performed.

Table 6.1 Priority and Rank of selected parameters

Category	Parameter	Priority (%)	Rank
1	Hydraulic Conductivity (HK)	23.4	1
2	Specific Yield (Sy)	12.5	4
3	Aquifer thickness (AT)	13.6	3
4	Drawdown (D)	10.6	5
5	Slope (S)	15.2	2
6	Drainage density (DD)	6.8	6
7	Geomorphology (G)	6.5	7
8	Land Use Land Cover (LULC)	4.2	8
9	Lineament Density (LD)	4.1	9
10	Topographic Position Index (TPI)	3.1	10

Hydraulic conductivity, Slope, Aquifer thickness, Specific yield, Drawdown, Drainage density and Geomorphology were the top seven priority parameters based on pairwise comparison. Their distribution in the study area is presented in **Figure 6.2**. The aquifer properties like HK, AT and Sy have been directly linked to the development of groundwater mound height and the amount of water that can be stored in the aquifer (Alkhatib et al. 2021), surface properties like slope, DD and geomorphology have been equally important in case of site selection based on GIS-MCDA techniques (Sallwey et al. 2019).

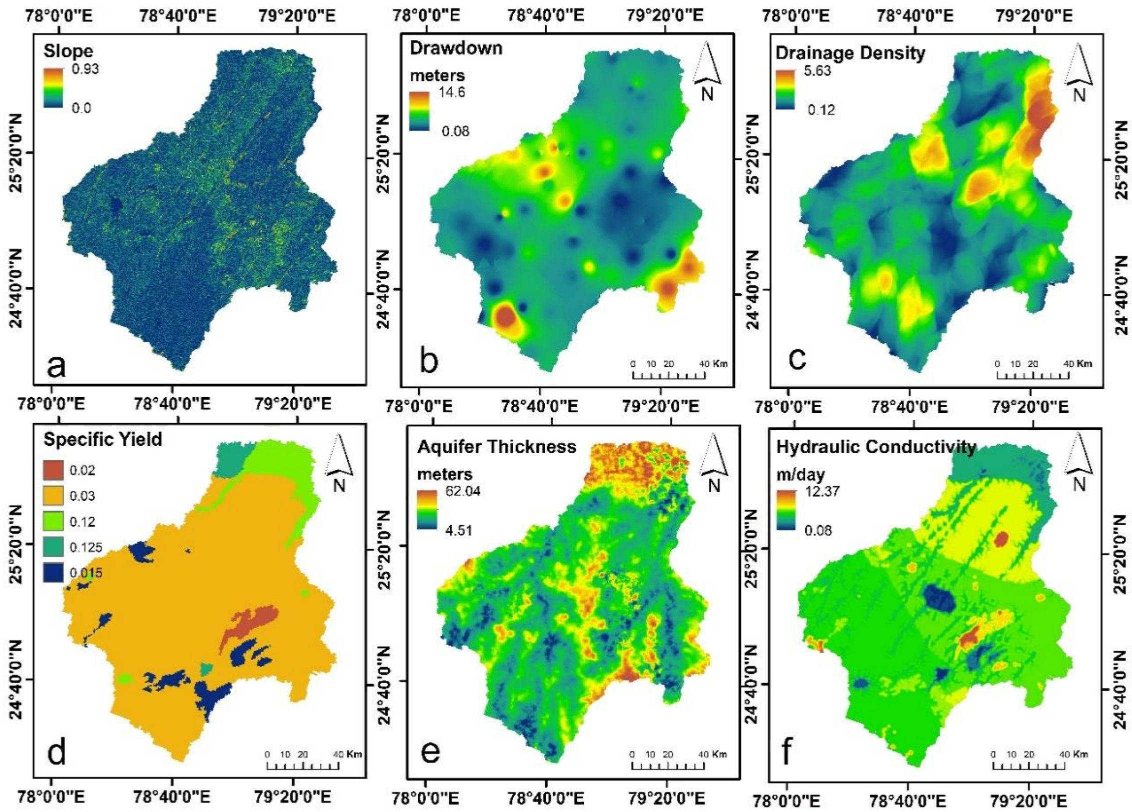

Figure 6.2 Distribution of surface and aquifer hydraulic parameters in the LBRB

Geomorphologically, the area was dominated by pediment pediplain complex with frequently distributed hills, valley, and plateau (**Figure 3.3**) while their distribution is given in **Figure 6.3**, where 1, 2 and 3 are low, moderate, and highly dissected hills and valleys; 4 is pediment pediplain complex which covered 80% of the area and 5, 6 and 7 were alluvial, flood plains and water bodies, respectively. Only first layer of the model was considered for artificial recharge, and it was covered by 50-60 m thick alluvial plains in the north and by 20-40 m thick pediplain complex in the rest (**Figure 6.2e**). Slope in the region varied from 0 to 18% and about 98% of the area was under 0 to 3.4% slope, considered under good category because of nearly flat terrain providing relatively high infiltration rate (Chowdhury et al. 2010). Drawdown was estimated as the overall change in head over 17-year time between pre and post monsoon (2003-2019). The mean drawdown in the region over the given period of study was around 2.8 m with a maximum of about 14 m along the south and s-west region (**Figure 6.2b**) which indicates the range of groundwater level fluctuations in the region. Drainage density (DD) is an inverse function of permeability, which indicates that if a surface is less permeable then water from rainfall will not infiltrate and consequently there will be more surface runoff. Due to this correlation of drainage density with surface runoff and permeability, it can be considered an indicator in identification of potential recharge sites (Chowdhury et al. 2010). DD was estimated as km/km^2 and about 47% of the area was under 1.56 /km DD considered as good for artificial recharge. The distribution of these parameters is as depicted in **Figure 6.3** with the red line indicating their cumulative percentage.

6.1.1.2. *K-Mean Clustering*

Clustering techniques have been used widely in groundwater management to reduce variables and to understand about the structure of the data (Mulligan and Ahlfeld 2016; Fienen et al. 2018). The K-means algorithm is an efficient and iterative clustering technique that attempts to divide the dataset into K unique non-intersecting clusters, with each data point belonging to just one group. It distributes data points to clusters in such a way that the total of the squared distances between the data points and the cluster's centroid (the arithmetic mean of all the data points in that cluster) is minimum. Lower the variation of data points within the clusters, more homogenous is the dataset within the cluster. Mathematically, the objective function can be denoted as:

$$J = \sum_{i=1}^{m} \sum_{k=1}^{K} w_{ik} \left\| x^{i} - \mu_{k} \right\|^{2} \qquad (6.3)$$

Where, $w_{ik}=1$ for data point x^i if it belongs to cluster K; otherwise, $w_{ik}=0$. Also, μ_k is the centroid of x^i's cluster.

Using the classical K-means algorithm, a multivariate clustering analysis was done based on different combinations of surface and aquifer hydraulic properties (**Table 6.2**). In each combination, while the aquifer properties were fixed the surface properties were varied to make 4 combinations of 5 properties (**Table 6.2**). It was done not only to understand their influence in the formation of clusters but also to reduce the computational time. The initial number of clusters was chosen as 20, based on the computational cost of the multivariate clustering and reported literature (Kim et al. 2004).

Table 6.2 Parameter Combination (PC) for Classical K-mean Clustering

Combination	**Parameters**				
	Aquifer properties			**Surface properties**	
PC1	HK	Sy	AT	D	S
PC2	HK	Sy	AT	S	DD
PC3	HK	Sy	AT	DD	G
PC4	HK	Sy	AT	G	D

As a process, K-means algorithm uses a distance-based calculation to assign optimal zones. It becomes computationally expensive to group data which have different units and scales of measurement. Datasets such as geomorphology were categorical, while few properties like drawdown and drainage density had anomalies in their scales. To overcome this problem, standardisation of datasets was employed, which had a mean of zero and standard deviation as one. This allowed the datasets to be inclusive of the multi-variate analysis. K-means being an unsupervised algorithm, can get stuck at local optima when there are noises in the datasets, or the 'K' centroids have not been properly defined.

To overcome this, the noises and redundancies were decreased before clustering. Different initializations of centroid have been tested and the one which generated lowest sum of squared error was selected. The standardised datasets are presented as histograms with their cumulative percentage (**Figure 6.3**). The graphical distribution of properties indicates the distribution of data points over the study area.

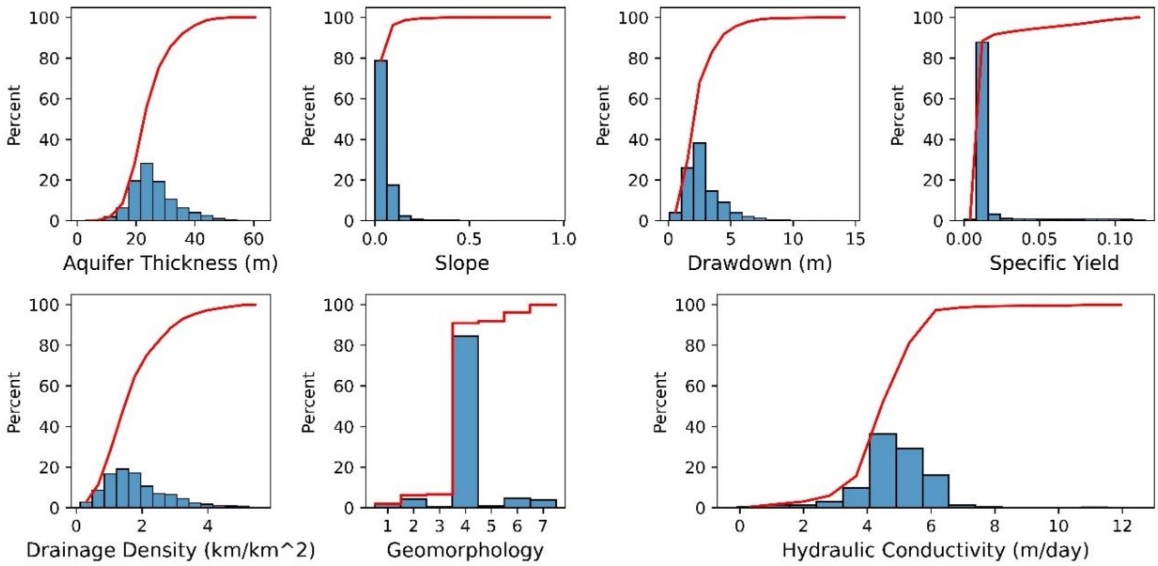

Figure 6.3 Histogram of standardised datasets for each parameter.

6.1.1.3. Groundwater Artificial Recharge

The calibrated MODFLOW-NWT model was used as management tool to assess the aquifer response to artificial recharge. Assessment of aquifer response at each grid cell would be computationally impossible and for this purpose, K-mean clustering technique was used to delineate areas having similar surface and aquifer properties. After discretising the study area into smaller clusters, the system was simulated to inject water at the centroid of each cluster one at a time. For clusters having an area of over 250 sq. km, multiple injection points were established. The surplus water due to excess surface runoff during the monsoon period has been taken as source water for artificial recharge. An average recharge rate of 600 m^3/d for 3 months post monsoon followed by 300 m^3/d for the next 2 months was considered, which amounted to 72000 m^3 volume of water being injected each year into the system.

6.1.2. Results and Discussion

6.1.2.1. Aquifer Clustering

Upon the application of K-means algorithm, the region having similar surface and subsurface hydraulic properties were clubbed together in the form of clusters based on selected surface and subsurface features. For each combination of selected parameters (**Table 6.2**) different profiles of clusters were created, given as Cluster Combinations (CC) (**Figure 6.5**). With regards to the size of study area, the limiting number of clusters was selected as 20, as suggested by Kim et al. (2004). To investigate the quality of clustering, Silhouette Index (SI) was employed. The Silhouette value measures how similar an object is to its own cluster compared to other clusters (Dudek 2020). It lies between -1 and 1 and if the value is close to 1, the sample is well clustered and vice-versa. For the different cluster, the obtained Silhouette value is presented in **Figure 6.4** and it ranges from 0.38 to 0.48. Although a better value of SI could have been obtained by selecting the optimal number of clusters, which was around 6 for this study, but it would have resulted in generation of larger clusters and detriment the objectives of this study.

The trivial and discrete clusters were merged into nearest equivalent cluster to generate 17, 20, 20, 18 cluster in each of CC1, CC2, CC3 and CC4 combinations, respectively. With the aquifer properties constant in each parameter combination, it was observed that the surface hydraulic properties greatly influenced the formation of clusters as each CC generated was unique, excluding a few which was existent in all the combinations (**Figure 6.5**). Distinct aquifer property (HK, Sy) as show in **Figure 6.2d** and **f,** from rest of the region influenced the common cluster formations. Low variations in slope (**Figure 6.2a**), drawdown (**Figure 6.2b**) or drainage density (**Figure 6.2c**) range in the

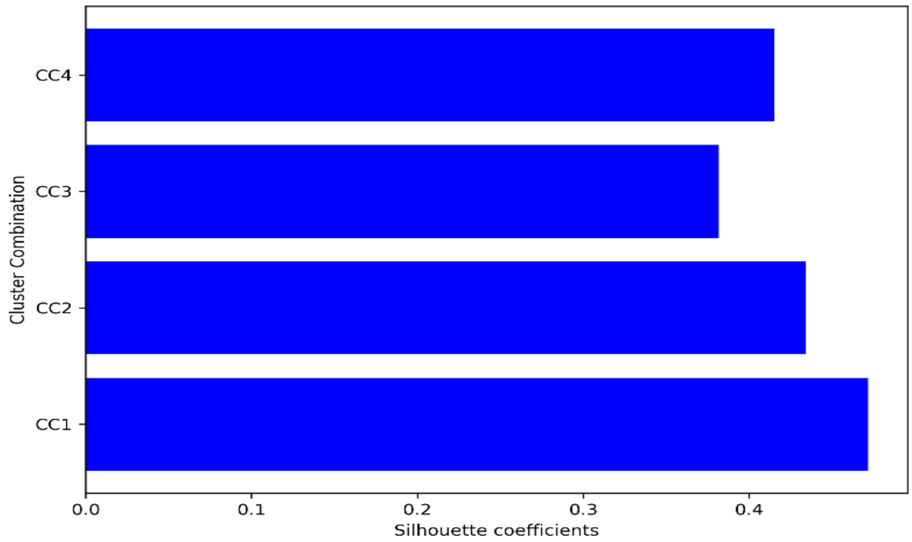

Figure 6.4 Silhouette Index values for four cluster combinations

study area, generated comparatively larger cluster (less members) in CC1 and CC2 than geomorphology and drawdown combination in CC3 and CC4. To show parameter values for each cluster would be a long and repetitive list, instead, the level of head change in each cluster was assessed.

6.1.2.2. Aquifer response to MAR

The aquifer response to MAR was assessed at the end of the stress period on the centroid of each cluster. It was based on the change in head (Δh) levels for the cell at which water was being injected. Clusters with lower Δh change would allow for more volume of water injection, with relatively less rise in head and would have the priority in case of MAR implementation site (Khalil et al. 2022). The response in head change was assessed individually for each cluster as to negate the influence of adjacent recharge points, in case of small clusters. For clusters with area larger than 250 sq. kms, multiple injection points were established to obtain an average rate of head change over the area. The distribution of cluster area in each head change range was represented as bar chart (**Figure 6.6**).

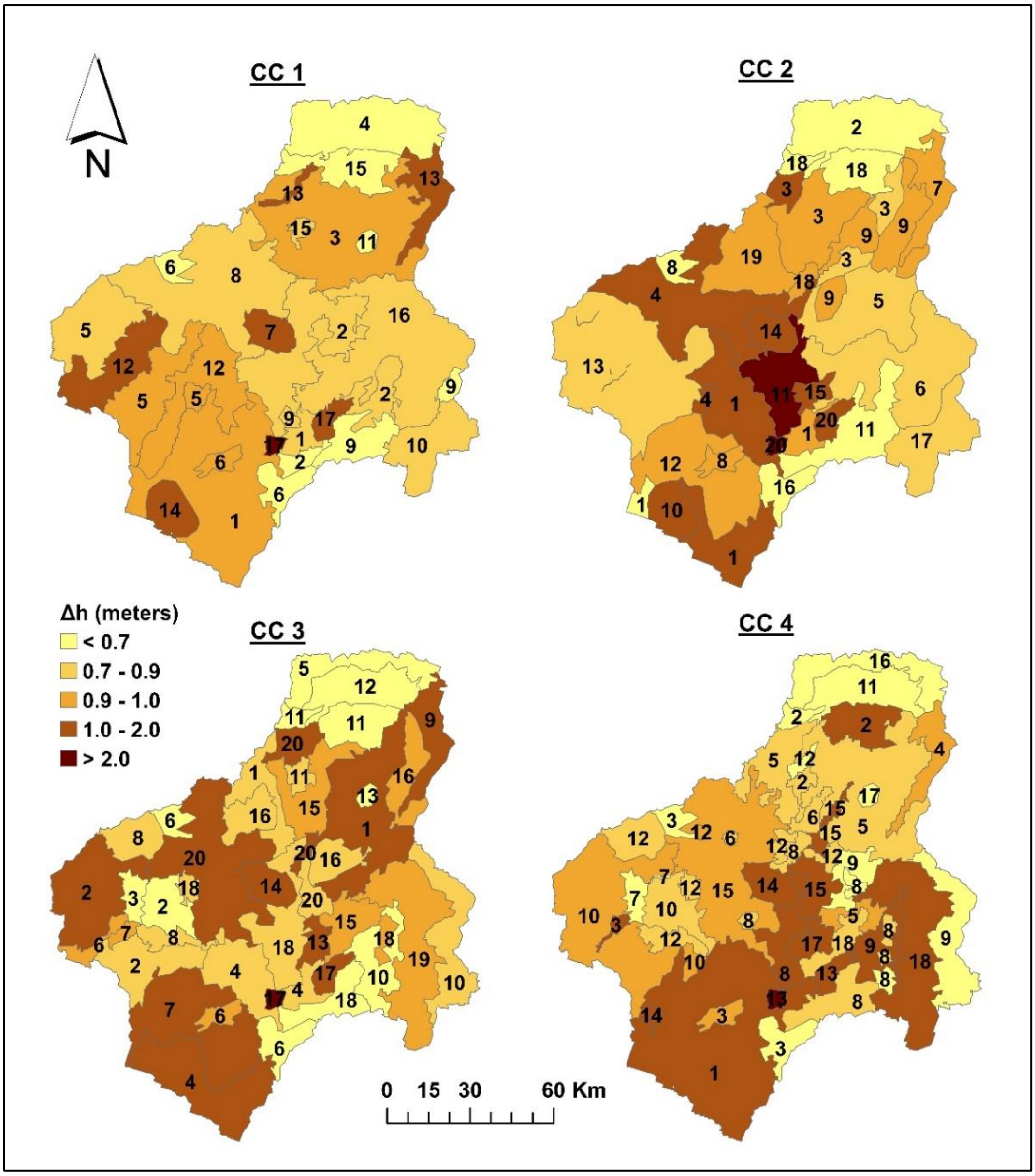

Figure 6.5 Cluster Combinations profiles with head change ranges.

For the selected rate of water injection, it was observed that clusters with Δh more than 2 meters was relatively negligible (<1%) in all 4 cases. Distinct distribution in spatial coverage was observed within each CC head change, with CC1 and CC2 having maximum area between 0.7-0.9 m Δh, while in CC3 and CC4, area with Δh (1.0-2.0 m) was more dominant. The maximum individually occupied area of over 41% within 1.0-2.0 m head change was observed in CC3. From the area distribution plots in each range of head change it can be inferred that along with the opted aquifer parameters (HK, AT, Sy) geomorphology

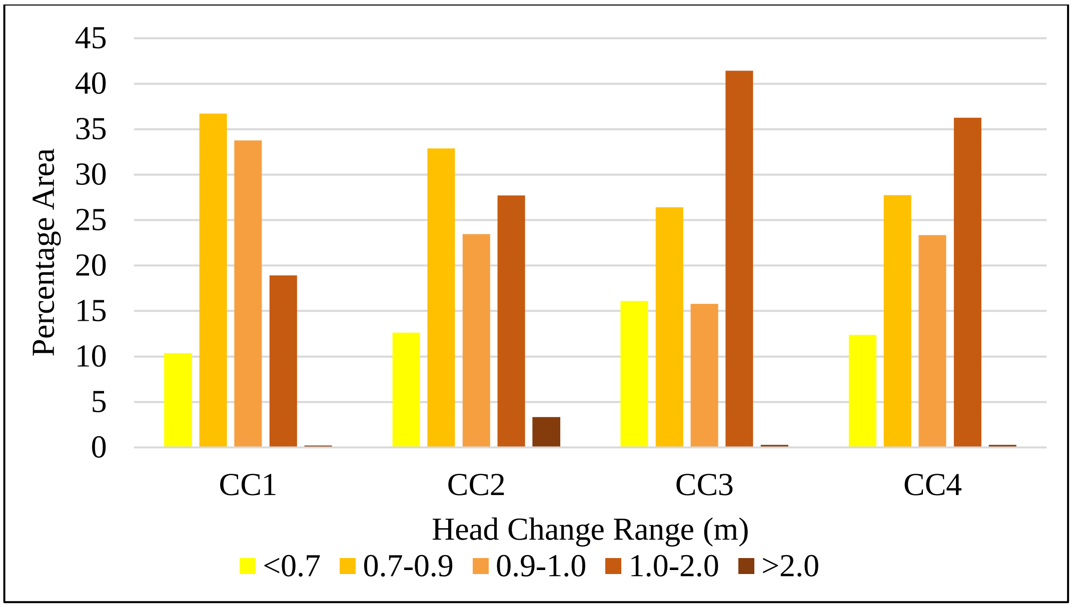

Figure 6.6 Percentage area distribution for range of groundwater head change.

and drainage density in CC3 and CC4 were the most influential surface parameters for generation of higher groundwater mound height than drawdown and slope parameters considered in CC1 and CC2.

The best cluster combination or the optimal site for MAR implementation would be the one which allowed for maximum infiltration with least change in groundwater mound height (Khalil et al. 2022). Among all the cluster combinations, CC3 had the maximum area spread (16%) under the least head change (<0.7 m) category and geomorphology and drainage density conjunction along with aquifer properties were found to be best suited combination for MAR site selection in case of LBRB aquifer systems. However, if the maximum allowable head change range is considered as one meter, then the cumulative area having head change lower than 1m would be maximum in CC1 with over 81% of the area under it. Larger available area could accommodate higher number of MAR structures, allowing for maximum volume of water to be infiltrated. Additionally, it signified that parameter combination of drawdown and slope along with aquifer parameters as the most suitable criteria. Thus, an inference can be drawn that the choice of parameter combination appeared to affect the range of groundwater head variation within the selected area in case of artificial recharge and that site-specific criteria of accepted head change ranges would determine the best possible parameter combination for site selection.

6.2. MAR Rate and Schedule

In the final step of the proposed MAR framework, the suitable recharge rates and the recharge schedule of the MAR process using surplus water is determined. The determination of suitable recharge rates usually depends on the recharge technique being adopted and the type of technique depends upon the source water and climate conditions at site (Alam et al. 2020). In this study, the surplus runoff generated after a rainfall event at 75% dependability has been taken as the source water for MAR. It is the second most common source of recharge water after rivers and its availability determines the recharge schedule of MAR. In order to avoid conflicts in water demand during events of low rainfall, or to maintain environmental and ecosystem flow, a minimum cut off for recharge water is required to be established. In case of recharge technique, in this thesis, MAR refers to the direct aquifer recharge through injection wells. Direct recharge of aquifers has the added advantage of less land requirement for installation, no clogging problem and water can be secured at target locations (Shandilya et al. 2022a).

Since the determination of recharge rates, operation schedule and recovery rates are more of site-specific design problem solved using field studies, much literature on recharge rates in case of injection wells is not available (Zhang et al. 2020). The formulas of flow in pumping wells are commonly adopted in practical applications based on the consideration that recharge is the reverse process of pumping (Zhang et al. 2020). For example, Dupuit's formula for steady-state flow in unconfined aquifer, Theim's formula for steady-state flow in confined aquifers or Theis's formula for calculating recharge rates in transient-state flow in confined aquifers (Kaledhonkar et al. 2003; Yu and Gong, 2001). Most of the undertaken modelling studies was based on assumed range of recharge rates that could be existent at field, based on the soil and hydrogeological characteristics of the site. However, suitable recharge rates can be established based on available surplus water and the permissible rise in groundwater table.

In this thesis, the suitable recharge rates into unconfined aquifers have been established based on the available surplus runoff estimated at 75% dependability and the permissible change in groundwater head through the application of PARC. The developed methodology was applied to Lower Betwa River Basin (LBRB) in central India to determine transient aquifer recharge rates and schedule and the overall effect of MAR implementation in the basin is also discussed.

6.2.1. Methodology

The suitable recharge rates (Q_{MAR}) refer to the sustainable injection capacity in aquifers based on the estimated PARC and surplus runoff values. The flowchart for suitable recharge rates estimation is given in **Figure 6.7**.

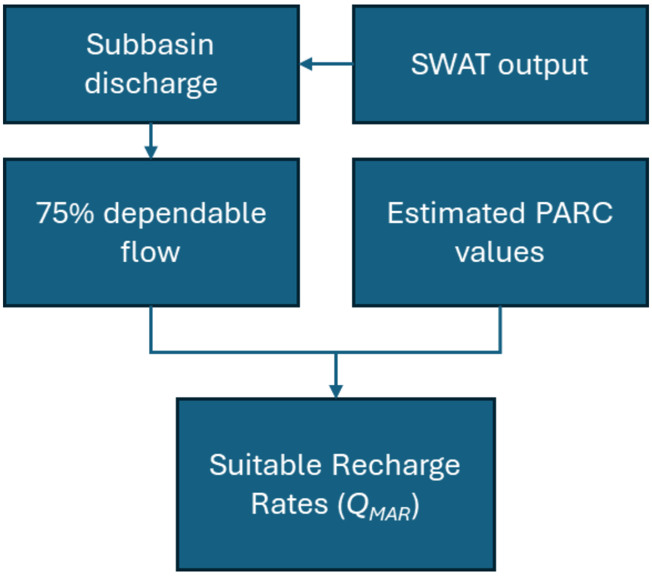

Figure 6.7 Methodology Flowchart for Suitable Recharge Rate determination

The selection process of appropriate recharge rates is further discussed using equations given below. The injection to the aquifer is scheduled for the duration when surface runoff is greater than the 75% dependable threshold. The suitable recharge rate through MAR at time period t ($Q_{MAR,t}$) can be defined through –

if $Q_{R,t} > Q_{th}$

$$Runoff\ excess\ (Q_{ex,t}) = Q_{R,t} - Q_{th} \tag{6.4}$$

and

$$Q_{MAR,t} = \begin{cases} PARC_t & PARC_t \leq Q_{ex,t} \\ Q_{ex,t} & PARC_t > Q_{ex,t} \end{cases} \tag{6.5}$$

Also if $Q_{R,t} \leq Q_{th}$

$$Q_{MAR,t} = 0 \qquad since,\ Q_{ex,t} = 0 \tag{6.6}$$

Where, the value $Q_{R,t}$ represents the runoff rate at time period t and Q_{th} represents the threshold flow rate at 75% dependable flow for the given subbasin. The runoff excess (Q_{ex}) at any time step cannot be negative and hence assigned as zero for cases in which the runoff rate is less than the threshold rate. **Eq. 6.5** compares the available excess runoff at the subbasin outlet to the PARC value. Since PARC limits the amount of recharge rate, if the runoff excess value exceeds the PARC, then PARC becomes the upper limit of the recharge rate. For cases where the surplus runoff is lower than the PARC, then all of surplus water can be recharged into aquifers. **Eq. 6.6** represents the unfavourable case where the generated runoff is less than the threshold flow rate. MAR in such cases will be avoided due to no adequate source of surplus water.

6.2.2. Results and Discussion

6.2.2.1. MAR Suitability

The PARC is sensitive to the aquifer transmissivity and the recoverable head (Δh) (Bouwer, 2002). The value of PARC will be higher for highly transmissive aquifer. The large recoverable head also represents the water deficiency at that location. A larger Δh can be recovered by large injection rate and the required rate will increase further for highly transmissive aquifer (Mao et al., 2011; Moench, 1997). It is safe to say that the PARC represents both, the aquifer characteristic as well as the groundwater deficiency.

For a site to be suitable for MAR, three main hydrological factors are required, (a) aquifer characteristics, (b) Groundwater deficiency and (c) the water availability (Rahman et al., 2013). PARC is dependent on the first two and the last one is calculated as surplus runoff generated in the basin. To generate a site suitability map, equal weightage is given to PARC and excess available runoff and weighted average of both the parameters has been calculated and normalised to get the suitability values. The MAR suitability values were classified into five categories using Natural Break method - Poor- (< 0.13), Moderate - (0.13-0.21), Fair - (0.21-0.32), Good - (0.32-0.53) and Excellent – (0.53 – 1.0) (**Figure 6.8**).

The results show that out of 768 subbasins in the modelled area, 316 subbasins were found to have the water table within 3 m below ground level and required no additional recharge, hence were excluded as balanced subbasins. The best site for MAR was those subbasins where ample of surplus water and adequate permissible aquifer storage was available, 15 of such subbasins showed excellent and 50 showed good suitability. The mean head change after injection, in these subbasins was about 1.98 m and could store about 162 Ham of injected water. The good category subbasins had the lowest mean PARC values

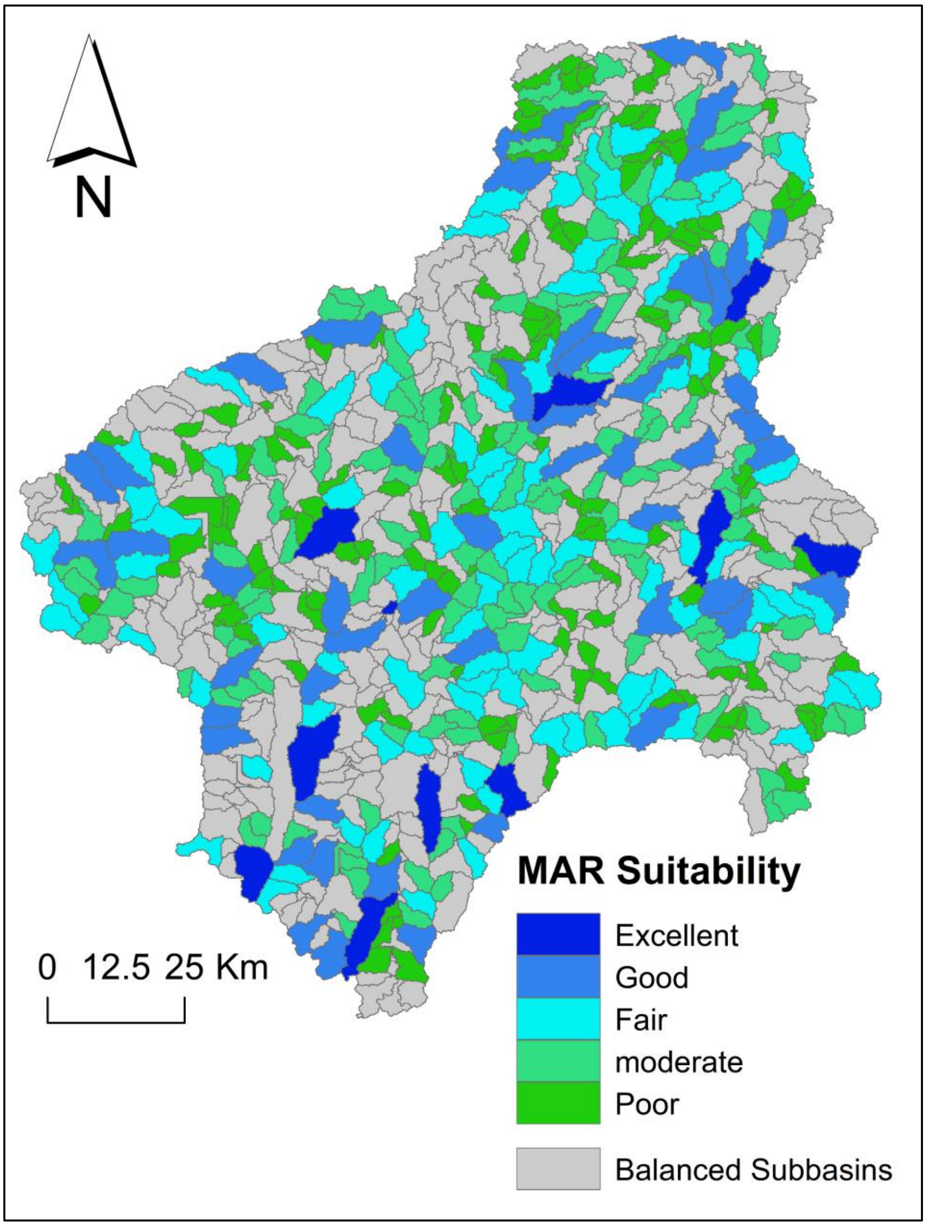

Figure 6.8 Suitable subbasins for MAR implementation

that allowed for low aquifer storage volume even when ample surplus water was available (**Figure 6.9**). About 150 of the selected subbasins had poor MAR suitability due to inadequate surplus water. It was observed that the area of the subbasins was directly corelated to MAR suitability preference as it improved with the increase in basin area due to the increase in runoff volume.

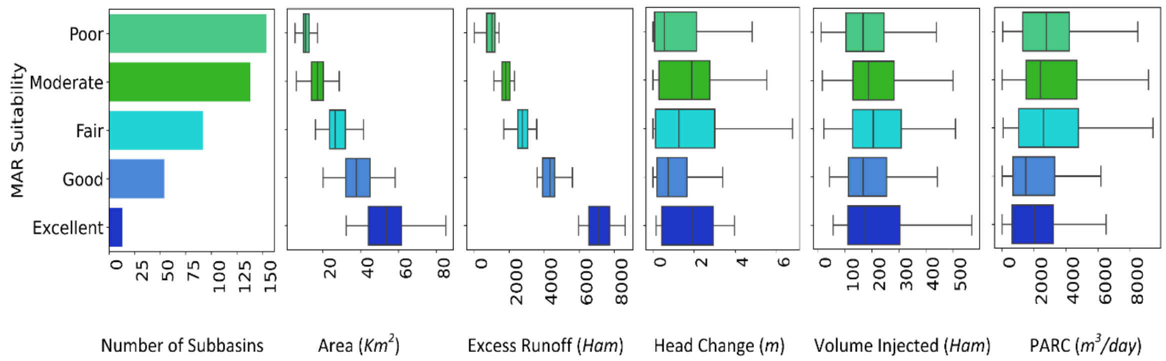

Figure 6.9 Frequency distribution of MAR suitability parameters in the LBRB

6.2.2.2. Suitable Recharge Rates and Schedule

The artificial recharge in the study area was simulated with a fully penetrating injection well. The MAR schedule was based on the availability of the surplus runoff, which was mostly concentrated during the monsoon months of June to September, and permissible recharge capacity of aquifers. The MAR schedule for each subbasin was prepared based on these criteria and added as supplementary file in **Appendix B**. The surplus runoff generation was mostly concentrated during the monsoon months of June to September. Apart from the low mean annual rainfall from 2005 to 2010, most of the years between 2003 to 2020 had runoff excess for at least two months (median value).

After the estimation of the PARC values for the scheduled durations, the suitable recharge rates were derived using **Eq. 6.4 – 6.6**. The distribution of suitable recharge rates varied from 0 to 9 Ham/day, with an average of 0.45 Ham/day (**Figure 6.10A**). About 10% of the subbasins had low recharge rates of under 0.1 Ham/day and 25% of the subbasins had a large recharge rate of over 0.5 Ham/day. There are 27 subbasin which had the average injection rate of more than 1.0 Ham/day. The monthly recharge rate time series has been plotted with one sample subbasins from each MAR suitability category (**Figure 6.10B-F**). The best suitable subbasins shows a consistence recharge operation while the number of recharge events decreases as the suitability decreases.

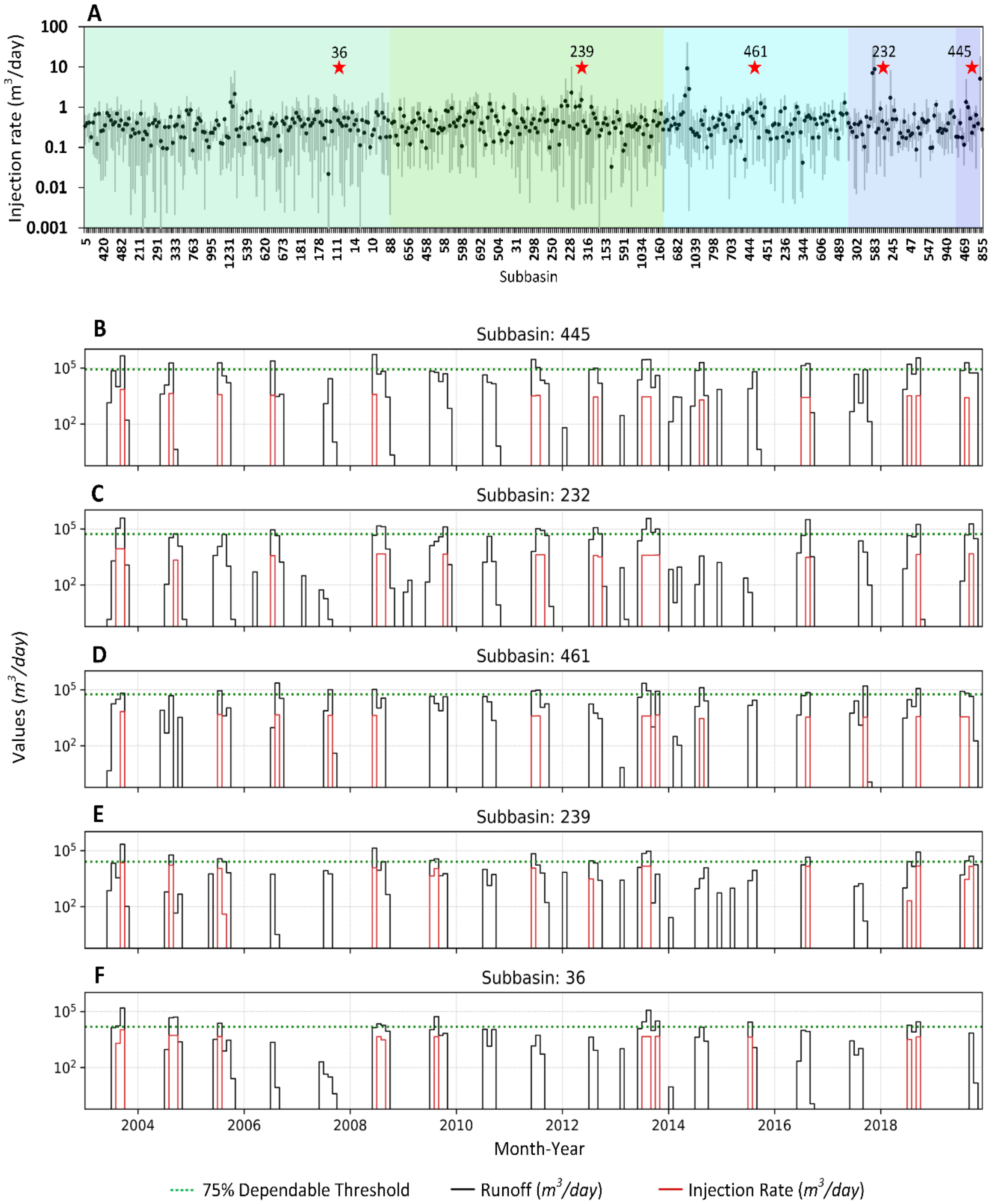

Figure 6.10 Estimated suitable recharge rates. ***A***. Mean recharge rate for each subbasin with its minimum and maximum range (the subbasins has been sorted by its suitability and shaded as per the MAR suitability category); [***B to F***]. Recharge rate through MAR and the generated surface runoff in the selected subbasin (marked in A).

6.2.3. Summary

Applications of clustering techniques effectively reduced the computational time while also considering the effect of surface and subsurface hydraulic properties. Different combinations of surface parameters along with aquifer properties were evaluated to prepare cluster combination maps to acknowledge their influence in cluster formations and consequently in site selection process. Optimal clusters were selected based on the height of groundwater mound created due to artificial recharge. Based on the head change range, the highest Δh values (> 2 m) was observed for clusters with low values of HK and Sy in all cluster combinations. CC3 synthesis of geomorphology and drainage density with aquifer values were the best combination under the least head change category (< 0.7 m) for the LBRB aquifers. In the next series of head change range (0.7-0.9 m and 0.9-1.0 m), it was CC1 that had maximum coverage of 47% and 81% respectively. Although, the requisite level of head change at site would determine the choice of parameter combinations to be considered, yet for this study it was the PC1 combination (HK, Sy, AT, DD and S) that allowed for maximum coverage of study area (81%) under minimum change in head (< 1 m).

The proposed method for optimal site selection provided in this study is applicable to other regions as well. Although, the application of such clustering techniques in tandem with numerical modelling was efficient in delineation of suitable MAR sites, detailed field investigation would be necessary to determine the quantity and source of water to be injected, the actual locations of MAR structure, and the befitting method of injection.

The applications of estimated PARC and surface runoff values was effective in estimation of suitable recharge rates and schedule across the LBRB. Analysis of the surface runoff it was observed that the surplus water was generally concentrated during the months of June to September in the LBRB. The suitability of a subbasin for MAR was determined based on the PARC and available surplus runoff of that basin. It was observed that 150 of the subbasins was under poor category i.e. either the surplus runoff was not adequate for groundwater recharge, or the permissible storage was not sufficient to store water. However, there existed 15 excellent and 50 good MAR suitability subbasins with low head change of about 1.98 m and could store about 162 Ham of injected water. While the most suitable subbasins showed consistent recharge operations throughout the study period, the recharge operations decreased with the decrease in MAR suitability. Overall, the study presented an effective way of determining suitable recharge rates based on available surplus water and permissible storage capacity, which could augment the field problem of recharge rate determination and could be an effective tool in MAR project planning.