Identification of drought in Dhalai river watershed using MCDM and ANN models

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An innovative approach for drought identification is developed using Multi-Criteria Decision Making (MCDM) and Artificial Neural Network (ANN) models from surveyed drought parameter data around the Dhalai river watershed in Tripura hinterlands, India. Total eight drought parameters, i.e., precipitation, soil moisture, evapotranspiration, vegetation canopy, cropping pattern, temperature, cultivated land, and groundwater level were obtained from expert, literature and cultivator survey. Then, the Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP) were used for weighting of parameters and Drought Index Identification (DII). Field data of weighted parameters in the meso scale Dhalai River watershed were collected and used to train the ANN model. The developed ANN model was used in the same watershed for identification of drought. Results indicate that the Limited-Memory Quasi-Newton algorithm was better than the commonly used training method. Results obtained from the ANN model shows the drought index developed from the study area ranges from 0.32 to 0.72. Overall analysis revealed that, with appropriate training, the ANN model can be used in the areas where the model is calibrated, or other areas where the range of input parameters is similar to the calibrated region for drought identification.

1. Introduction

Drought is a hydrological phenomenon where the demand of water exceeds its supply from few favourable sources for a considerable time in a specific region (McKee *et al.* 1993). According to the United States (US) weather bureau, drought is the period of dry weather of sufficient length and severity to cause at least partial crop failure. The India Meteorological Department (IMD) defines drought condition when the rainfall deficiency in any area is more or equal to 26% of long term normal rainfall (Shewale and Kumar 2005; Kendale 2012). The criteria adopted by Central Water Commission (CWC),

India is followed by the Irrigation Commission in 1972 for drought identification, i.e., drought is a situation when the annual rainfall is less than 75% of the average in 20% of the years examined. The major cause of meteorological drought is the occurrence of below normal precipitation, which is affected by various natural phenomena. Most likely causes of occurrence of drought are either decreasing level of precipitation, ground water, vegetation cover or increased evapotranspiration (Kumar 2012). In India, severe drought conditions in most of the river basins are observed in the summer season *albeit* there is high precipitation with high surface runoff (Van Loon *et al.* 2014).

Keywords. Multi-criteria decision making; artificial neural network; drought identification.

Identification of drought at a precise level has drawn considerable attention due to its disastrous effect on society across the world. It is significant for hydrological analysis and water resource management. Monitoring of precise drought areas through field investigation alone is time consuming, costly, and complicated. This problem is scientifically tricky from a hydrological point of view. Normally, drought is quantified based on duration, severity, location in absolute time, areal coverage and the ratio of severity to duration (Dracup *et al.* 1980). Palmer (1965) has argued that the drought is considered as meteorological phenomena and can be evaluated as a meteorological anomaly characterised by a prolonged and abnormal moisture deficiency. Moreover, in the majority of studies, other parameters like evapotranspiration, streamflow, soil moisture, vegetation canopy, and groundwater data were generally used for drought identification. Usually in drought identification, hydrologic variables, such as annual and monthly precipitation, canopy cover, soil moisture, temperature, evapotranspiration, stream flows have been extensively modelled using linear techniques, such as autoregressive moving average with exogenous inputs (Salas *et al.* 1985).

Advance Remote Sensing (RS) data derived from Satellite Remote Sensing (SRS) have been used to study the drought situation in large extend area through multiple band data (Aher and Dalvi 2012; Aher *et al.* 2014). The National Oceanic and Atmospheric Administration (NOAA), which manages operational meteorological satellites, have designed a new Advanced Very High Resolution Radiometer (AVHRR) based Vegetation Condition Index (VCI) which has been shown to be a good tool for drought detection and tracking (Kogan 2008). Similarly, AVHRR satellite data was used for calculating the Normalized Difference Vegetative Index (NDVI) and the Water Supplying Vegetation Index, which are useful indices for the estimation of vegetation health and drought monitoring (Jain *et al.* 2009). Parida *et al.* (2013) used the RS-based Soil Moisture Index (SMI), rainfall anomaly data from the Tropical Rainfall Measuring Mission (TRMM), and rice production data for drought detection and validation. In addition to these 250 m, NDVI dataset from Moderate-resolution Imaging Spectroradiometer (MODIS) dataset has opened a new avenue of the identification and prediction of drought (Wan *et al.* 2004; Zhao and Running 2010). Practitioners have generally accepted these methods during the past several decades. Thus, in drought identification method, the threshold levels of considered factors are needed to be determined.

The use of Multi-Criteria Decision Making (MCDM) and Artificial Neural Network (ANN)

model is increased due to its decision making capacity through quantitative manner. Two of the most significant methods of MCDM are Analytic Hierarchy Process (AHP) and Analytic Network Process (ANP). The AHP method proposed by Saaty (1980) for solving socio-economic decision making problems. AHP is utilized when dimensions are independent, and is suited to solve the problems involving dependent dimensions (Yang *et al.* 2008; Zolekar and Bhagat 2015), while ANP also proposed by Saaty (1996) provides a method for input judgment and measurement to derive ratio scale priorities for the distribution of influence between the different parameters. It was subsequently used for generation of the multi-level hierarchical structure of objectives, criteria, sub-criteria and alternatives (Evangelos and Stuart 1995). In many industrial engineering applications, the final decision is based on an evaluation of a number of alternatives in terms of a number of criteria. This problem may become very difficult when the criteria are expressed in different units or the pertinent data are difficult to be quantified. In drought study, it is necessary for hydrologists to consider alternative models when nonlinearities are important and play a significant role.

The ANN is an alternate computational approach inspired by studies of the brain and nervous systems (McCulloch and Pitts 1943). The main theme of ANN research focuses on modelling of the brain as a parallel computational device for various computational tasks that were performed poorly by traditional serial computers. The ANN model is powerful prediction tool for the relation between drought and its parameters. Moreover, the ANN models have been used increasingly in various aspects of science and engineering because of its ability to model both linear and nonlinear systems without the need to make some assumptions as are implicit in most traditional statistical approaches (Riad and Mania 2004). ANN models are nonlinear mathematical structures that have the ability to show the nonlinearity in the process for communication between inputs and outputs of any system (Hsu *et al.* 1995). It works with software for searching the best network algorithm to predict the results with synthesis and recognition, adaptive interfaces among parameters data for the index prediction. ANN has shown great ability in modelling and forecasting nonlinear and non-stationary data in hydrology and water resources engineering due to their innate nonlinear property and flexibility for modelling (Dawson and Wilby 2001). Desalegn and Babel (2011) have developed a nonlinear stream flow forecasting model using ANN model at the Awash River, Ethiopia. ANN provides a comprehensive and rational framework to define the structure of a decision problem, to represent

and quantify its parameters chosen for the study and to evaluate alternative solutions (Saaty and Peniwati 2013).

In view of these, in this attempt, MCDM and ANN models are used for drought-prone region identify along with an advance Drought Index Identification (DII) in the upper Dhalai river watershed in Tripura. The objective of this attempt was to develop a methodology for drought prone region identification using MCDM and ANN models from surveyed drought parameters. In this area, use of MCDM and ANN model was carried out first and reported for drought identification and its validation. Developed methodology is an innovative quantitative approach for precise drought identification in the areas where the model is calibrated or other areas where the range of input parameters are similar to the calibrated region.

2. The study area

The north-eastern region of the Indian subcontinent is rich in natural resources. Geologically, this region is underlain by unconsolidated sand, gravel, sandstone, conglomerate, and fractured limestone, which does not support to retain runoff as surface water. Thus, the water holding capacity is not enough in sub-surface layer (Kendale 2012). In this region there is also increasing levels of urbanisation and changes in land use/cover pattern. Therefore, the water retention capacities of the most of the watersheds in these areas are decreasing. Similarly, there is a prevalent state of

changes in climatic characteristics during the last few decades and its impact was profound. The Dhalai river (or Dhala river) is sharing the considerable length of the common boundary between India and Bangladesh. It rises in the mountains of Tripura in large, dense forest and enters Kulaura Upazila of Maulvi Bazar District of Bangladesh. The study area covers 550 km². The north–south and east–west areal extent are around 37 and 15 km, respectively (figure 1). The general slope is from the south to the north direction, with an average of 7.5°. In the eastern and western directions, having linear-shaped hills, have an average of 350–400 m elevated from mean sea level. Numerous streams and rivulets that originate from the neighbouring hills debouch into the Dhalai river (figure 2). The terrain is dissected by a hilly topography with patches of the plain region formed by deposition of sediment, and exhibit a wide array of sedimentary rocks characteristics of marine-mixed-fluvial type origin (Ghosh *et al.* 2013). These sediments were deposited in the Surma basin during the late Cenozoic time in a wide range of environmental conditions governed by the local tectonic movement (SER 2002). Such geological formation is influencing the sub-surface groundwater holding capacity of the local region. The whole basin is mainly composed of weathered sandstone, shale, siltstone and alluviums (Ghosh *et al.* 2013) (figure 3). The average annual rainfall is around 3000–4000 mm, though most part of the upper Dhalai faces the water scarcity problem in summer seasons due to intense runoff and percolation during monsoon.

Figure 1. Location map of the upper Dhalai river basin.

Figure 2. Dhalai river along with tributaries draped over a digital elevation model.

Figure 3. An alluvial reach of Dhalai river near Kulai locality (July 2014).

3. Materials and methods

3.1 Drought parameter identification and ranking

Parameters associated with drought were collected from expert, literature, and cultivator survey. A total of 50 experts' (researchers) surveys were carried

out to identify significant drought parameters. Suggested parameters from experts were ranked according to their relative weight calculated using equation (1).

$$S_E = \frac{A \times (a_m/a_t)}{A_t}, \quad (1)$$

where S_E is the parameters score for the expert survey, A is the number of experts who have suggested this parameter, a_m is assigned as most important parameters, a_t is assigned as least important parameters and A_t is total surveyed experts.

Literature survey was carried out from a total of 50 articles linked to drought (Palmer 1965; Dracup *et al.* 1980; McKee *et al.* 1993; Wan *et al.* 2004; Shewale and Kumar 2005; Jain *et al.* 2009; Zhao and Running 2010; Kendale 2012; Ghosh *et al.* 2013; Parida *et al.* 2013). Parameters accountable for drought were identified from the literature. Identified parameters were ranked according to their relative weight calculated from equation (2).

$$S_L = \frac{l}{L}, \quad (2)$$

where S_L is the parameters score for literature survey, l is the number of articles in literature included this parameter and L is the total number of surveyed articles in the literature.

Cultivator survey was also carried out from total 12 cultivators, considering that cultivators have huge experience of drought in the local study area. IRRI (2016) stated that thousands of farmers in the drought-prone Tripura province welcomed the release of 16 new varieties of various crops, including nine rice varieties for different ecosystems. These ecosystems include drought-prone lowlands and uplands. The parameters suggested by cultivators were also ranked according to their relative weight calculated from equation (3).

$$S_c = \frac{c}{C}, \quad (3)$$

where S_c is the parameter's score for cultivators' survey, c is the number of cultivators that suggested this parameter and C is the total number of cultivators surveyed.

Identified drought parameters from expert, literature and cultivator survey were used for relative weighting. The ranks were allowed to select the parameters according to their relative weight using equation (4) and the top eight weighted parameters were selected.

$$S_A = \frac{C1 + C2 + C3}{3}, \quad (4)$$

where S_A is an alternative (parameter) score, $C1$ is a score of the parameter in 1st criterion (expert),

$C2$ is a score of the parameter in 2nd criterion (literature) and $C3$ is a score of the parameter in 3rd criterion (cultivator).

3.2 Use of MCDM model

Selected experts', literature and cultivators' criteria were ranked for AHP and ANP and implementation of MCDM. Weight of expert (E) criteria using equation (5), weight of literature (L) criteria using equation (6) and weight of cultivators (C) criteria using equation (7) was calculated and were assigned the relative ranks.

$$E = \frac{E}{E + L + C} = \frac{50}{50 + 40 + 12} = 0.49 \quad (\text{Rank 1}) \quad (5)$$

$$L = \frac{L}{E + L + C} = \frac{40}{50 + 40 + 12} = 0.39 \quad (\text{Rank 2}) \quad (6)$$

$$C = \frac{C}{E + L + C} = \frac{12}{50 + 40 + 12} = 0.11 \quad (\text{Rank 3}) \quad (7)$$

Pairwise comparison matrix (PCM) was then prepared from these three main criterion weights. From the obtained weight of three criteria, geometric mean was calculated (table 1). Then, the supermatrix was prepared from the PCM. The weights

Table 1. Pair-wise comparison matrix (PCM) for criteria.

	E	L	C	Geometric mean	Normalization
E	1/1	2/1	3/1	1.82	0.2577
L	1/2	1/1	3/2	0.91	0.0322
C	1/3	2/3	1/1	0.61	0.0094

Table 2. Super matrix of AHP and ANP.

	Criteria				AHP weight	AHP normalization	ANP weight	ANP normalization
	(C1)	(C2)	(C3)					
A1	0.3687	0.3664	0.3729	AHP weight	0.11032	0.35108	0.36981	0.32747
A2	0.0921	0.1280	0.1864		0.02961	0.09423	0.14226	0.12597
A3	0.1778	0.0916	0.0616		0.04935	0.15705	0.10428	0.09234
A4	0.1288	0.1832	0.0932		0.03997	0.12719	0.12876	0.11402
A5	0.0737	0.0450	0.1238	ANP weight	0.02161	0.06876	0.08705	0.07709
A6	0.0608	0.0732	0.0745		0.01873	0.05959	0.07008	0.06206
A7	0.0521	0.5180	0.0410		0.2783	0.09704	0.17703	0.15676
A8	0.0457	0.0605	0.0462		0.01416	0.04506	0.05003	0.0443
					=0.31422	1 (Validation)	= 1.1293	1 (Validation)

of all the parameters were multiplied with each criteria weight (weight of criteria (PCMs) $\times$ weight of parameters) in AHP. A similar process was carried out in ANP. Validation of supermatrix was carried out through normalisation of AHP and ANP weights and its summation equal to one (table 2).

3.3 Drought index

Final weights of drought parameters were calculated from AHP and ANP weight average. Similarly, random values were prepared from final weight of parameters in a Microsoft excel sheet. The drought index was generated from final weight of parameters and random values using equation (8) and trained in the ANN model (table 3).

$$\text{Index} = IA \times Ip \quad (8)$$

where IA is the actual index and Ip is the predicted index.

3.4 Training of ANN model

Drought index training was computed in Alyuda NeuroIntelligence software for nonlinear ANN model development with seven algorithms: (1) Quick Propagation, (2) Conjugate Gradient Descent, (3) Quasi-Newton, (4) Limited-Memory Quasi-Newton, (5) Levenberg Marquardt, (6) Online Back Propagation, and (7) Batch Back Propagation for searching the best neural network. The training process of Limited-Memory Quasi-Newton algorithm was shown along with multiple steps of testing and query (figure 4).

3.5 Data collection

The selected Upper Dhalai Watershed (UDW) was divided into 66 grids with two interlaced $3.17 \times 3.46 \text{ km}^2$ grids for grid-wise data collection.

Table 3. Final weight, random values and drought index.

	A	B	C	D	E	F	G	H	Index
1	0.3310	0.1481	0.1199	0.0915	0.0888	0.0648	0.0562	0.0425	
2	Precipitation	Soil moisture	E. transpiration	Vegetation canopy	Cropping pattern	Temperature	Cultivated land	Groundwater level	0.286640
3	0.2350	0.5205	0.2342	0.0587	0.5076	0.2400	0.4174	0.3354	

Hydrological and meteorological data for each grid from UDW were collected from various primary and secondary sources. The average precipitation data for the year 2013 were collected from IMD, evapotranspiration and temperature data were collected from online data sources like the Worldclim data (<http://www.worldclim.org/>), and AccuWeather data (<http://www.accuweather.com/en/in/india-weather>) for the year 2013. Dhalai district administrative website was also used for cross-verification of precipitation and temperature data. Land use/cover information was extracted from a Landsat image, acquired on December 2013 using Erdas Imagine 9.1 image processing software to know the vegetation canopy, cropping pattern and cultivated land information. Soil moisture data were extracted from 13 soil samples, collected in May 2013 in UDW. Soil moisture (%) was measured with the help of electronic balance from equation (9).

$$S_M = \frac{x - y}{x} \times 100, \quad (9)$$

where S_M is soil moisture (%), x is the total weight of soil (wet) and y is the weight of soil (dried).

The obtained soil moisture data from 13 soil samples were interpolated using the kriging method in Surfer software. Kriging is a geostatistical interpolation technique, which estimates unknown values with a specific probabilistic distribution at an arbitrary point of the space (Deshmukh and Aher 2016a, b). Average water table data from the Katalutma, Ambasa, Abhanga, Balaram and Halhuli stations were collected in the year 2011 from central ground water board website. Similar kriging interpolation method was used for groundwater table data interpolation in UDW. Geostatistical interpolation of sampled data using Geographical Information System (GIS) software provides the information or data of unknown area or points within the selected area (Deshmukh and Aher 2014).

3.6 Drought indexing and identification

The actual drought index was prepared from experts', literature, and cultivators' survey data with the help of MCDM and ANN models. Meanwhile, the predicted index was also prepared from grid-wise collected data of UDW. Collected data of eight parameters for 66 grids of UDW were used for drought index development and its preparation using developed Limited-Memory Quasi-Newton algorithm (neural network). It was better than the commonly used training method because of minimum actual root errors, 0.004863 as

Figure 4. Detailed hierarchical process in the ANN model. (a) Dataset error, (b) network error, (c) error distribution, (d) actual vs. output and (e) resultant graph.

compared to other algorithms. Collected parameter data were normalised considering a direct relationship of parameters and drought (maximum temperature–maximum drought), as well as an indirect relationship of parameters and drought

(high precipitation–minimum drought) using equation (10).

$$A_N = \frac{\text{Actual} - \text{Min}}{\text{Max} - \text{Min}}, \quad (10)$$

Figure 5. Input (actual) and output (predicted) index.

Figure 6. Detailed flow chart of the methodology.

where A_N is the normalised parameter, ‘Actual’ is the value selected for normalisation, ‘Min’ is the lower value of parameters in all grids and ‘Max’ is the maximum value of parameters in all grids.

Developed ANN model, Limited-Memory Quasi-Newton algorithm and collected data of UDW were finally used for drought-prone region identification in the UDW study area. Drought index was developed and predicted from collected database from 66 grids in the study area. The actual and predicted drought index was used for drought identification in the selected area (figure 5). Data of

all parameters were mosaic in the GIS software for final drought area identification in the UDW study area. Figure 6 shows the detailed flow chart of the methodology.

4. Results and discussions

4.1 Drought parameters and weighted ranking

From the experts’, literature and cultivators’ survey, eight significant parameters were obtained and

Table 4. *Drought parameters and its weighted ranking.*

Sl. no.	Parameter	Score				Rank
		Experts	Literature	Cultivator	Average	
1	Precipitation	2	0.7	0.87	1.17	1
2	Soil moisture	0.3	0.6	0.75	0.55	2
3	Evapotranspiration	0.8	0.5	0.25	0.51	3
4	Vegetation canopy	0.46	0.6	0.41	0.49	4
5	Cropping pattern	0.2	0.3	0.58	0.36	5
6	Temperature	0.13	0.5	0.33	0.32	6
7	Cultivated land	0.13	0.4	0.16	0.23	7
8	Groundwater level	0.08	0.4	0.16	0.21	8

Table 5. *Final weight of parameters.*

Parameters	AHP weight	ANP weight	Final weight	Rank
Precipitation (A1)	0.3511	0.3109	0.3310	1
Evapotranspiration (A3)	0.1570	0.1391	0.1481	2
Vegetation canopy (A4)	0.1272	0.1126	0.1199	3
Cultivated land (A7)	0.0970	0.0859	0.0915	4
Soil moisture (A2)	0.0942	0.0834	0.0888	5
Cropping pattern (A5)	0.0688	0.0609	0.0648	6
Temperature (A6)	0.0596	0.0528	0.0562	7
Ground water level (A8)	0.0451	0.0399	0.0425	8

Table 6. *Trained index using algorithms (ANN model).*

Neural network training	Mean level after index training			
	Target	Output	AE	ARE
Quick propagation	0.4728	0.472798	0.005921	0.014948
Conjugate gradient descent	0.4728	0.472826	0.002068	0.005365
Quasi Newton	0.4728	0.472763	0.002017	0.004957
Limited Memory-Quasi Newton*	0.4728	0.47276	0.001909*	0.004863*
Levenberg Marquardt	0.4728	0.473535	0.005149	0.012363
Online back propagation	0.4728	0.473247	0.008286	0.021116
Batch back propagation	0.4728	0.472781	0.010027	0.025477

AE: actual error, ARE: actual root error, *: Minimum actual error and actual root error.

Figure 7. DII using (a) direct method and (b) ANN and MCDM model.

ranked according to the relative weight of parameters. Precipitation significantly correlated with drought, while the ground water level was less correlated with drought, according to revealed weightage (table 4).

4.2 MCDM model

Selected experts', literature and cultivators' criteria were also ranked for AHP and ANP processes in the MCDM. Ranking of criteria was obtained as expert – 0.49 (rank 01), literature – 0.39 (rank 02), and cultivator – 0.11 (rank 03) from the PCM. According to the mean score of the parameter from AHP and ANP, precipitation has the highest score (0.3310), while groundwater level found the lower score (0.0425). Therefore, relative rank to precipitation is first to be considered and then other weighted rank parameters can be taken into account (table 5).

4.3 ANN model development, testing and validation

The obtained index from AHP and ANN in supermatrix were trained with different algorithms.

Results obtained from different algorithms training are presented in table 6. The best neural network was found to be the Limited-Memory Quasi-Newton where the actual error was 0.001909 and actual root error was 0.004863, which was minimum compared to other trained algorithms (table 6).

Drought index was prepared using a developed ANN model with the best neural network. Parameter data (grid-wise) from UDW were used to compare the actual drought conditions in the study area (Appendix 1). The actual drought index and the predicted drought index were generated after the training and by collecting a database of UDW in the developed limited-memory Quasi-Newton network. Based on collected data and use of the limited-memory Quasi-Newton network, actual and predicted drought index were developed. The composite range of indices is 0.22–0.76 and 0.32–0.72 for the present study area (figure 7). In the actual index, the maximum affected area is identified in the south central part, which is indicated by greater than 0.6 index value, while the minimum drought-affected region is the east-central section of the study area. In the predicted index, maximum drought effects were identified in the northern-central section of the watershed, while

Figure 8. Gridded drought index for the upper Dhalai river basin.

the minimum was found in the east-west marginal boundary UDW (figure 7).

4.4 Drought identification

The present area is havocked by several drought phases with variable intensity in overall areas. The prime characteristic of entire collected or gathered drought parameter data is its inherent nonlinearity. The developed Limited-Memory Quasi-Newton algorithm was better than the commonly used training method for drought identification. Based on primary and secondary collected data and the quantitative database from MCDM and ANN models, grid-wise drought-prone regions were identified in UDW of Tripura hinterland (figure 8). It was based on direct relationships, as the maximum index value indicated the maximum intensity of drought, while the minimum index value indicated the minimum intensity of drought. According to this approach, the maximum drought-affected area was identified in the northern part, while relatively minimum droughts in the middle and south-west sections of the UDW study area

(figure 8). The grid-wise variations in the drought index value ranging from 0.32 to 0.72 might be due to local topography, slope and nature of the land use and land cover in the present area. It can be argued that near the river channel the intensity of drought is less.

5. Conclusions

In this study, an ANN model was developed and trained to identify the grid-wise drought prone area using MCDM model and selected parameter data. Based on eight drought parameters from expert, literature, and cultivator survey, the ANN model was trained. The trained ANN model was tested in the mesoscale upper DRW in Tripura hinterlands, India. The obtained results have depicted that the Limited-Memory Quasi-Newton algorithm was better than the commonly-used training method for these types of area. Results obtained from the ANN model, 0.32 to 0.72 are the drought index that has developed for the present study area (figure 8). It has been generally argued that near the river channel the problem of water scarcity would be less. Using climatic and other data set and subsequently some nonlinear model, it has been observed that the potential zone for the problem of water is near the river channel. Validation with data outside of the upper DRW recommended that the ANN model trained with data from the upper DRW had better predictive potential when there are similar types of input data. Moreover, predictive precision was considerably reduced and recalibration of the ANN model's parameters may be required if the input data were dissimilar. Overall, the analysis revealed that with appropriate training, the ANN model can be used in the areas where the model was calibrated, or other areas where the range of input parameters is similar to the calibrated region.

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Appendix

Table A1. *Parameter data for upper Dhalai watershed (66 Grids).*

Grid no.	Latitude	Longitude	P (cm)	T (°C)	V (%)	C (%)	E	S.M. (%)	CP	G (M)
A1	91.7703	24.1349	235	27	93.2	4.3	5.38	3.74	1	1.6
A2	91.7964	24.1353	225	28	53.1	41.66	4.54	3.74	1.5	1.6
A3	91.8279	24.1356	223	28.1	67.01	29	4.92	6.8	1	1.6
A4	91.8587	24.1357	226	28	71.23	20.9	5.04	7.9	1.5	1.6
A5	91.8902	24.1354	238	27.4	96.03	2.2	5	8.12	1	2.1
A6	91.9222	24.1370	244	27.7	97.05	1.1	4.83	8.12	1	2.1
B1	91.9216	24.1105	241	27.7	94.91	2.1	5.24	8.4	1.5	2.1
B2	91.8905	24.1109	256	27	95.1	1.9	4.4	8.4	1.5	2.1
B3	91.8590	24.1110	227	27.9	72	23.11	4.9	8.8	2	2.1
B4	91.8276	24.1109	221	28	47.98	48.32	4.85	8.7	2	2.1
B5	91.7963	24.1099	225	28	63.4	32.18	4.9	5.3	2	1.6
B6	91.7674	24.1098	238	27.8	98.03	1	4.96	5.3	1.5	1.6
C1	91.7674	24.0797	241	27.7	98.9	0.2	4.95	5.7	2	1.9
C2	91.7965	24.0795	224	27.9	69.09	26.67	4.92	5.7	2	1.9
C3	91.8284	24.0790	222	28	44.98	51.9	5.02	7.55	2.5	2.3
C4	91.8594	24.0792	229	27.8	73.01	19.99	5.21	9.15	2	2.6
C5	91.8903	24.0797	243	26.9	99.02	0.1	4.82	7.9	2	2.6
C6	91.9220	24.0793	240	27.9	89	3.12	4.9	7.9	2	2.6
D1	91.9224	24.0484	237	27.6	93.83	5.01	4.69	6.08	2	3.1
D2	91.8906	24.0481	251	27.3	99.04	0.02	4.92	6.08	2.5	3.1
D3	91.8591	24.0484	227	27.8	75.09	19.26	4.99	4.9	3	3.1
D4	91.8276	24.0484	223	28	51.66	44.33	5.03	5.9	2.5	3.05
D5	91.7963	24.0482	227	27.9	86.7	9.23	5	5.08	3	2.5
D6	91.7661	24.0481	255	27.6	98.8	1.01	4.98	5.08	2.5	2.6
E1	91.7661	24.0168	257	27.5	98.69	0.9	5.07	4.2	3	2.3
E2	91.7976	24.0171	227	27.9	79.9	15.12	4.29	4.2	3	2.3
E3	91.8284	24.0171	227	27.9	64.09	31	5.02	4.1	3	3
E4	91.8587	24.0173	230	27.7	81.22	12.22	4.73	4.2	3.5	3.1
E5	91.8907	24.0169	251	27.1	96.45	2.99	5.19	4.9	2	3.1
E6	91.9216	24.0171	235	27.8	93.67	3.77	4.89	4.9	3	3.1
F1	91.9217	23.9854	242	27.6	98	1.3	4.8	4.7	3.5	3
F2	91.8903	23.9856	241	27.9	96.9	1.2	5.38	4.7	3.5	3
F3	91.8585	23.9858	228	27.9	59.71	32.11	4.54	3.7	3	3
F4	91.8279	23.9857	224	27.9	51.1	40.05	4.92	4.1	3.5	2.5
F5	91.7964	23.9858	227	27.9	77.89	18.03	5.04	3.7	4	2.1
F6	91.7666	23.9861	248	27.5	97.03	1.2	5	3.7	4	2.1
G1	91.7666	23.9548	272	27.4	98.01	1.09	4.83	3.4	3.5	1.8
G2	91.7967	23.9555	230	27.9	94.3	8.9	5.24	3.4	4	1.8
G3	91.8283	23.9551	225	27.9	39.81	54.07	4.4	5	4	2
G4	91.8598	23.9546	229	27.8	73.05	12.9	4.9	5.8	3.5	2.4
G5	91.8908	23.9541	238	27.6	92.1	4.11	4.85	5.2	4	2.4
G6	91.9219	23.9540	258	27.5	97.9	0.3	4.9	5.2	4.5	2.4
H1	91.9218	23.9235	254	27	98.1	1.2	4.96	5	4	1.4
H2	91.8903	23.9235	235	27.7	92.98	4.12	4.95	5	4.5	1.4
H3	91.8584	23.9228	229	27.8	66.19	28.02	4.92	6	4.5	1.04
H4	91.8277	23.9230	231	27.9	61.05	32.98	5.02	4.4	4	1.3
H5	91.7972	23.9232	236	27.7	97.4	1.9	5.21	2.45	4.5	1.6
H6	91.7656	23.9231	272	27.4	97.8	0.8	4.82	2.45	4.5	1.6
I1	91.7658	23.8915	254	27.5	97.97	0.3	4.9	2.4	4	1.6
I2	91.7976	23.8915	237	27.5	95.12	2.5	4.69	2.4	4.5	1.4
I3	91.8287	23.8922	231	27.7	86.7	9.8	4.92	4.4	4.5	1.3
I4	91.8599	23.8920	235	27.7	85.29	7.9	4.99	6	4	1.5
I5	91.8912	23.8918	239	27.6	87	11.29	5.03	5	4.5	1.5
I6	91.9215	23.8919	249	26.9	98.05	0.4	5	5	4.5	1.5

Table A1. (Continued).

Grid no.	Latitude	Longitude	P (cm)	T (°C)	V (%)	C (%)	E	S.M. (%)	CP	G (M)
J1	91.9218	23.8595	246	27.4	96.5	1.1	4.98	5	4.5	1.5
J2	91.8903	23.8610	237	27.5	93.9	4.1	5.07	5	5	1.5
J3	91.8601	23.8607	235	27.6	89.09	7.91	4.29	6	5	1.5
J4	91.8279	23.8611	234	27.6	88.5	7.34	5.02	6	5	1.5
J5	91.7968	23.8603	234	27.7	85.11	12.23	4.73	2.4	5.5	1.6
J6	91.7646	23.8605	253	27.5	97.8	1.1	5.19	2.4	5.5	1.6
K1	91.7664	23.8284	231	27.7	96.46	2.7	4.89	2.4	4.5	1.6
K2	91.7970	23.8291	231	27.8	97.1	1.05	4.8	2.4	5	1.6
K3	91.8291	23.8296	231	27.7	97.98	1.9	5.38	6	5.5	1.3
K4	91.8576	23.8307	239	27.6	96.93	1.01	4.54	6	5	1.4
K5	91.8928	23.8295	243	27.5	92.71	5.02	4.92	5	4	1.4
K6	91.9223	23.8294	246	27.4	96.92	2.1	5.04	5	5	1.4

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