Int.J.Curr.Microbiol.App.Sci (2023) *12*(07): 119-132

International Journal of Current Microbiology and Applied Sciences
ISSN: 2319-7706 **Volume 12 Number 7 (2023)**
Journal homepage: http://www.ijcmas.com

Original Research Article https://doi.org/10.20546/ijcmas.2023.1207.014

Estimation of Soil Temperature and Moisture Using STM Model in Varanasi District of Uttar Pradesh, India

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Keywords

STM Model, Soil Moisture, Soil Temperature, Gross Domestic Product (GDP)

Article Info

Received: 01 June 2023
Accepted: 04 July 2023
Available Online: 10 July 2023

A B S T R A C T

The STM2 is a simple and potentially useful tool for modeling soil moisture and temperature conditions to plan agricultural management operation. The quality of STM2 soil moisture estimates varies with soil textural groups. The model worked best with the Sandy and Loamy soil textural groups, which had the lowest RMSE values and the highest d indices. Its moisture estimates were only moderately good for the Clayey soil, and they were unacceptable for the Gravelly soil. Addition of data on the percentage of coarse fragments in the soil or PTFs based on gravelly soil types would probably improve soil moisture prediction. The quality of soil temperature estimates was not as dependent on the soil textural group. In fact, the performance of the model was better for temperature than moisture at all soil types. The quality of soil moisture estimates also generally decreased with increasing depth. Weeds germinate at shallow depths; thus, the model was not designed to estimate conditions at greater depths.

Introduction

Agriculture plays a key role in overall economic and social well-being of India. Though the share of agriculture in both Gross Domestic Product (GDP) and employment has declined over time, the pace of decline in its share in employment has been much slower than that of GDP. The share of agriculture in GDP is declined from 39% in 1983 to 24% in 2000–01 compared with much lower rate of decline in its share in total employment from 63% to 57% during the same period. In this era of 'every drop counts' soil moisture is a valuable parameter to be considered for study and research purposes.

Soil moisture is considered an integral and fundamental part of the climate system and is among the key variables of hydrological cycles over the globe. SMC is a key variable in balancing the ecosystem although it is found in a small volume that too is bound within the fractures present in the soil. Soil moisture and temperature classification is a foundation for many modern international soil classification systems. It is recognized at virtually all levels of Soil Taxonomy (Soil Survey Staff, 1999).

Soil moisture and soil temperature properties influence soil-plant relationships and serve as a determinant of the chemical, mechanical, and biological processes that occur in the soil. (Christopher C. Cochran, 2010). Factors influencing soil moisture and temperature at any given point on the landscape are: percent slope, aspect, albedo, vegetative cover (type and amount), relative humidity, runoff, soil depth, soil texture, soil mineralogy, soil bulk density, elevation, latitude, percent possible sunshine, day length, wind speed, temperature, and precipitation. These interrelationships are commonly not considered when assessing soil temperature and moisture. Since current soil climate models are regional in nature, this has often resulted in erroneous soil moisture and temperature classifications, especially in areas of the country with high relief (Newhall and Berdanier, 1996).

Modern methods like remote sensing provide an opportunity to measure soil moisture directly for an extensive range of vegetation, results were found to have errors within permissible ranges. Wide ranges of sensors are found to be working in different regions for the determination of soil moisture. One of the prime advantages of this technique is that it can provide better resolution of spatial and temporal measurements and precise insight into the soil moisture present at a particular depth of soil profile.

In this era of evolving technology, several models have been introduced for agriculture research purposes. This saves the cost of extensive involvement of laborers as well as valuable time. Availability of STM Model 1D provides the user real-time soil moisture data with the availability of certain parameters as input, soil moisture can be simulated at different depths and can be used for various analyses. In brief, the objectives can be summarized as:

Assessment of insitu meteorological and observed soil moisture dataset with seasonal variations.

Materials and Methods

The whole methodology of research is divided into 5 different phases as follows:

Experimental site preparation

Soil analysis

Collection of ground station data

Crop data collection

Numerical simulation and Model Performance

The percentage of different constituents was calculated as follows-

%Clay = (hydrometer reading * 100)/wt of sample

%Silt = (corrected hydrometer reading at 40 sec*100)/(wt of sample) - %clay

%sand = 100% - %silt - %clay

Model Description

The STM2 was developed by Spokas and Forcella (2009) to predict topsoil microclimate to prevent weed propagation (weed seed germination) in the context of sustainable soil and crop management. The model is available free from the USDAARS.

To generate soil moisture and temperature estimates, STM2 requests primary soil properties (sand, clay, and organic matter percentages) and daily meteorological data (total rain and minimum and maximum air temperature) as inputs (Spokas and

Forcella, 2009). It is worth noting that STM2 is not a multilayer model: soil moisture and temperature estimates are generated for different soil depths using data from only one soil layer (e.g., topsoil or weighted means).

The STM2 is a one-dimensional model that considers only vertical water and thermal balances. The model also requires that the user define the initial water potential and, as lower boundary conditions (at the bottom of the soil profile), water potential and temperature.

The STM2 uses pedotransfer functions (PTFs) to generate secondary soil properties from soil texture and organic matter %. Water and thermal balances take into account evaporation and precipitation fluxes, solar heating, surface ponding, runoff, and infiltration. The STM2 outputs for a given depth are volumetric water content (soil moisture) or soil water potential and soil temperature. Model estimates can be produced at several different time intervals (weekly, daily, twice per day, four times per day, or hourly). Daily estimates were used in our study.

Relative root mean square error

This statistical indicator is used to predict the accuracy of the model simulation. The RMSER value of zero is considered a perfect match between the observed and modeled datasets. However, it is practically impossible in most cases. The increased value of this indicator reflects the greater deviation of predicted values from the observed datasets. It is obtained by dividing the RMSE values by the mean of the observed datasets.

$$RMSER = \frac{\sqrt{RMSE}}{Omea}$$

Model Parameterization

A number of parameters must be set before running STM2. Because the model was developed for estimation of the soil surface microclimate, it does not consider changes in soil texture with profile depth. In fact, as mentioned above, it does not utilize multiple layer or horizon inputs. For this reason, we used a weighted average of primary soil properties from the surface to the depth of estimation. The soil profiles used in our study contained a series of similar (homogenous) horizons. When soil profiles vary in terms of soil texture layers, the impact of using a weighted average on the secondary soil properties estimated by the pedotransfer functions must be investigated. We selected warm, temperate, rainy (humid) as the climate type for our region and set the average wind speed to light breeze. In the model variables section, the depth of the soil profile was set to 1 m and the mean annual air temperature was used as the lower temperature boundary condition, as suggested. A value of −500 kPa was used for the soil moisture lower boundary condition. Lower boundary condition values are specific to each soil profile, and the best way to determine them is to use moisture measurement averages or to calculate them using iterative numeric methods to find the optimal value to minimize estimation error. Schutte *et al.,* (2008) chose the latter approach. At the time of this study, the source code for this procedure was not available. To determine the initial soil moisture potential value, Mumen (2006), who tested a similar model (TEC), suggests starting the model 24 h after an important rain event and applying a value of −10 kPa. The main reason for this choice is that it is not necessarily true that soil is saturated after a rain event: soil water content tends to reflect the field capacity. The solar heating, evaporation, and evaporation scaled by humidity options were enabled (default), and the runoff option was set to the default value of 50%.

Results and Discussion

Soil properties

Physical properties of soil

For simulating the soil hydraulic properties, certain physical parameters of soil were required to be calculated, either through laboratory experiments or by direct field measurements. These soil properties were used as input in STM2. All these properties of the soil were found to be constant in all the simulations, as the same experimental plot was selected in all the seasons for planting and growing the crops. Soil properties obtained are shown in Table 3.1.

Hydraulic properties of soil

With the help of soil physical parameters, hydraulic properties of soil were simulated. This was done, by putting all the obtained values in Neural Network Prediction window available in STM2. This Neural Network Prediction (Hilten, Lawrence *et al.,* 2008) simulates the values of hydraulic properties of a given soil profile with the help of Rosetta Lite. The used version for this research is 1.1 (Schaap, 2001). In case of unavailability of direct field measurement instruments or laboratory methods for obtaining the required soil physical properties, a series of soil catalogs are available in the rosetta. Different textural classes are also displayed for simulating the hydraulic properties.

The van Genuchten functions have been consulted to simulate the required parameters (Van Genuchten, 1980) along with Mualem pore distribution (Mualem, 1976). The various hydraulic parameters which were simulated by rosetta are, residual water content of soil (θr), saturated moisture content of soil (θs), parameters in water retention function of soil (α) as well saturated hydraulic conductivity for soil profile (Ks). As per the required simulations performed in rosetta, various parameters of hydraulic properties obtained at different depths are presented in Table 3.2.

Simulation of soil moisture for different crop seasons

Four crop growth seasons were selected for soil moisture simulation comprising of alternative *Kharif* and *rabi* seasons in the span of two years (2018-2020). Based upon the crop planted in each season at the field, irrigation and crop growth data were gathered accordingly. Graphical Plots of meteorological parameters were obtained for each season to have a comparative insight of the values obtained from ground station and satellite.

For each season, two simulations were executed, first using meteorological parameters (simulation 1) obtained using ground station data and second obtained using satellite data (simulation 2). Therefore, eight simulations were accomplished out in total. Hydra probe data of soil moisture was recorded at different depths of its installation and was used as standard observed data.

A comparison-based study was done by plotting the weather parameter graphs to study and understand the difference in recording meteorological datasets by ground station and satellite and to analyze the effect of these differences on soil water simulation by using STM2.

Comparative graphs were plotted for individual seasons to study the pattern of soil moisture distribution at three different depths and its variation due to weather, crop growth, and irrigation datasets. The comparison also included irrigation to understand the sensitivity of the model.

Each selected crop had a different duration of growth and root uptake mechanism. Analysis of each season was done separately to understand the nature and variation of modeled soil moisture in contrast with observed datasets.

Simulation for *Rabi* season

The very first season chosen for soil moisture simulation was of *Rabi* (01/10/2018 to 31/12/2018) during which wheat was planted at the experimental plot. The duration of the crops selected for simulation was of 90 days. Crop data were recorded at each significant growth day such as vegetative, reproductive, and ripening. Water was added to the field at each crop growth stage and suitable irrigation interval. Although irrigation was not provided at each day, during which only precipitation was considered as an input for water added to the field. Root depth penetration and plant height were noted at each growth stage. For the simulation of water flow, this model considered precipitation, evaporation, transpiration from crop and root water uptake into account.

Simulation 1 was established using ground station data and simulation 2 was performed using satellite data. Graphical as well as the statistical analysis was done to draw the important conclusions for modeling the SMC.

Figure 3.2 suggests that simulated water content is mostly over estimated in crucial crop growth stages. In both cases of simulation (ground station and satellite), modeled soil moisture was found greater in value. During the last few days of the crop, the model was found to be under estimating the SMC. A similar pattern of over estimation was observed at the depth of 5 cm and 20 cm of the soil profile.

However, an agreeable match was found at each depth between the ground station and satellite simulation. It could be due to less deviation of meteorological parameters obtained from ground station data from satellite data. With the increasing number of crop growth days, a great deviation was seen in the observed and modeled soil moisture at all the three different depths of soil moisture.

Higher values of this deviation were seen at the depth of 50cm.One of the conceivable reasons for the acquired deviation could be improper recording and unavailability of accurate field irrigation data.

Also, water added to the field at individual crop growth stages was random. However, great coordination between the ground station and satellite simulation was observed at the depth of 5 cm and 20 cm.

Another reason might be the spatial variation in soil properties within the field of experiment. Sand, silt, and clay composition were not uniform at a deeper depth (Qiao, 2014) and soil properties were varying to a great degree.

Simulation for *Kharif* Season

The next season chosen for soil moisture simulation was *Kharif* (June 2019- October 2019). The field was mostly planted with rice. Other crops like soy bean, arhar, moong bean, etc were sown at the adjacent plots.

All these crops had different water requirements and root penetration depth. Irrigation along with the rainfall was obtained to gather accurate data for providing total water added to the field.

Variation of meteorological parameters

Comparison of simulated and observed soil moisture

Figure3.4 shows that model is under estimating the water flow during the initial growth phase of the crop at the depth of 5 cm and 50 cm. However, higher values of over estimation were found at the depth of 50 cm during the initial days of the growth period of the rice. In the middle of the growth stages, mostly at the reproductive stage, observed moisture is well synchronized to the simulated moisture at all three depths. Graphical analysis at all the depths depicts that simulation 2 is over estimating at the depth of 50 cm. The valid reason could be the higher values of meteorological parameters such as wind speed and relative humidity obtained from the satellite (Jiang, Pang *et al.*, 2010).

Almost after 90-100 days of crop sowing, the simulation was under estimated. The justifiable reason could be the lower values of water broadcasted to the field. During the ripening phase of the rice, irrigation was reduced as water received through rainfall fulfilled the water necessity of the crop planted at the field.

Fig.1 Diagrammatic representation of the experimental design

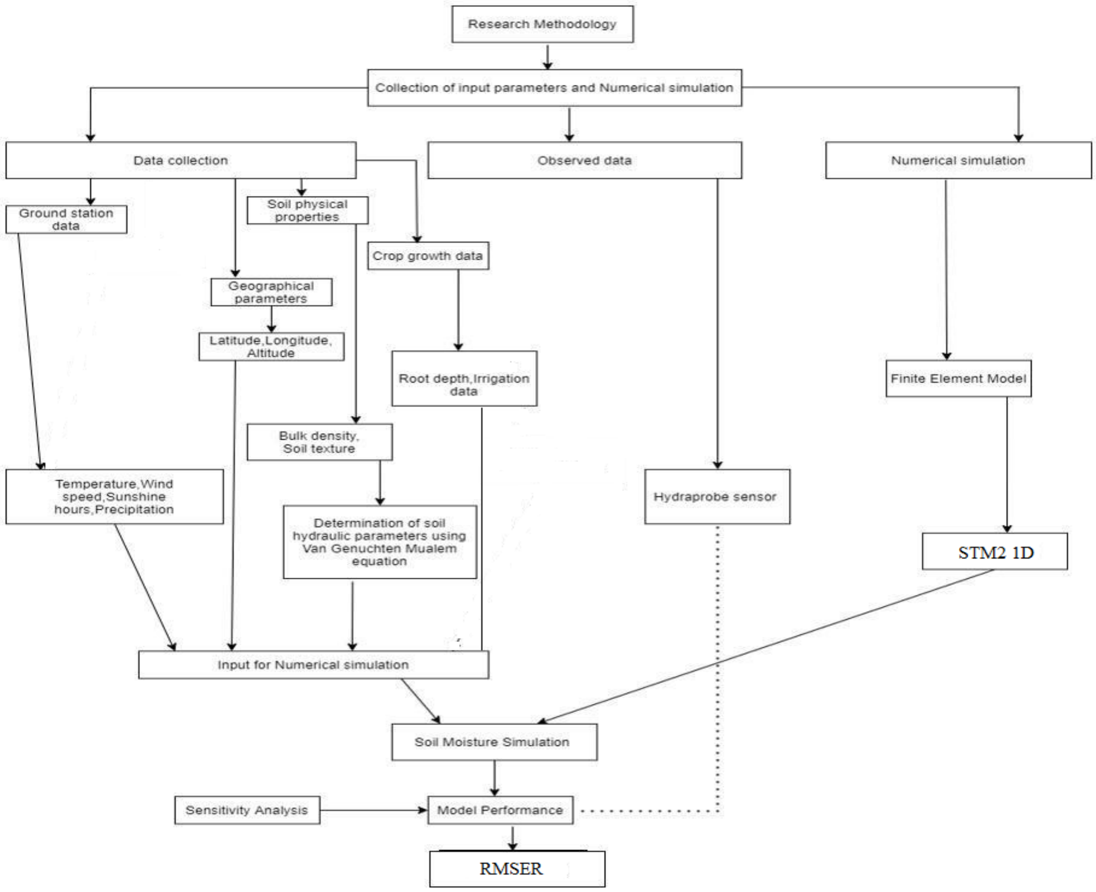


Table.1 Overview of traditional methods of soil moisture measurement

Methods	Advantages	Limitations	Time taken
Gravimetric	High accuracy	Time insensitive	About 24 hour
Neutron Scattering	Suitable for several depths	Radiation is hazardous	About 1-2 minutes
TDR	Easy to use	Sensitive to saline soils	Instantaneous
Gamma attenuation	Non-destructive	Restricted up to a depth of 2.5cm	Instantaneous
Tensiometer techniques	Durable and easy to operate	Estimation is fragile	About 2-3 hour

Table.2 Remote sensing techniques for soil moisture measurement

Methods	Advantages	Limitations
Optical Remote Sensing	High resolution (spatial)	Crop cover sensitive
Thermal Remote Sensing	Large area is covered	Poor resolution(temporal)
Active Microwave RS	Cost-effective	Sensitive to roughness
Passive Microwave RS	Provides global scale soil map	Coarse resolution(spatial)

Table.3 Parameters of soil physical properties

Depth (cm)	Sand (%)	Silt (%)	Clay (%)	Bulk Density (g/ cm^3)
0-5	41.88	19.86	38.25	1.35
5-20	39.38	17.59	43.02	1.40
20-45	38.44	16.55	45.01	1.48
45-50	38.79	17.15	44.05	1.53

Fig.2 Meteorological parameters, obtained from meteorological station and satellite

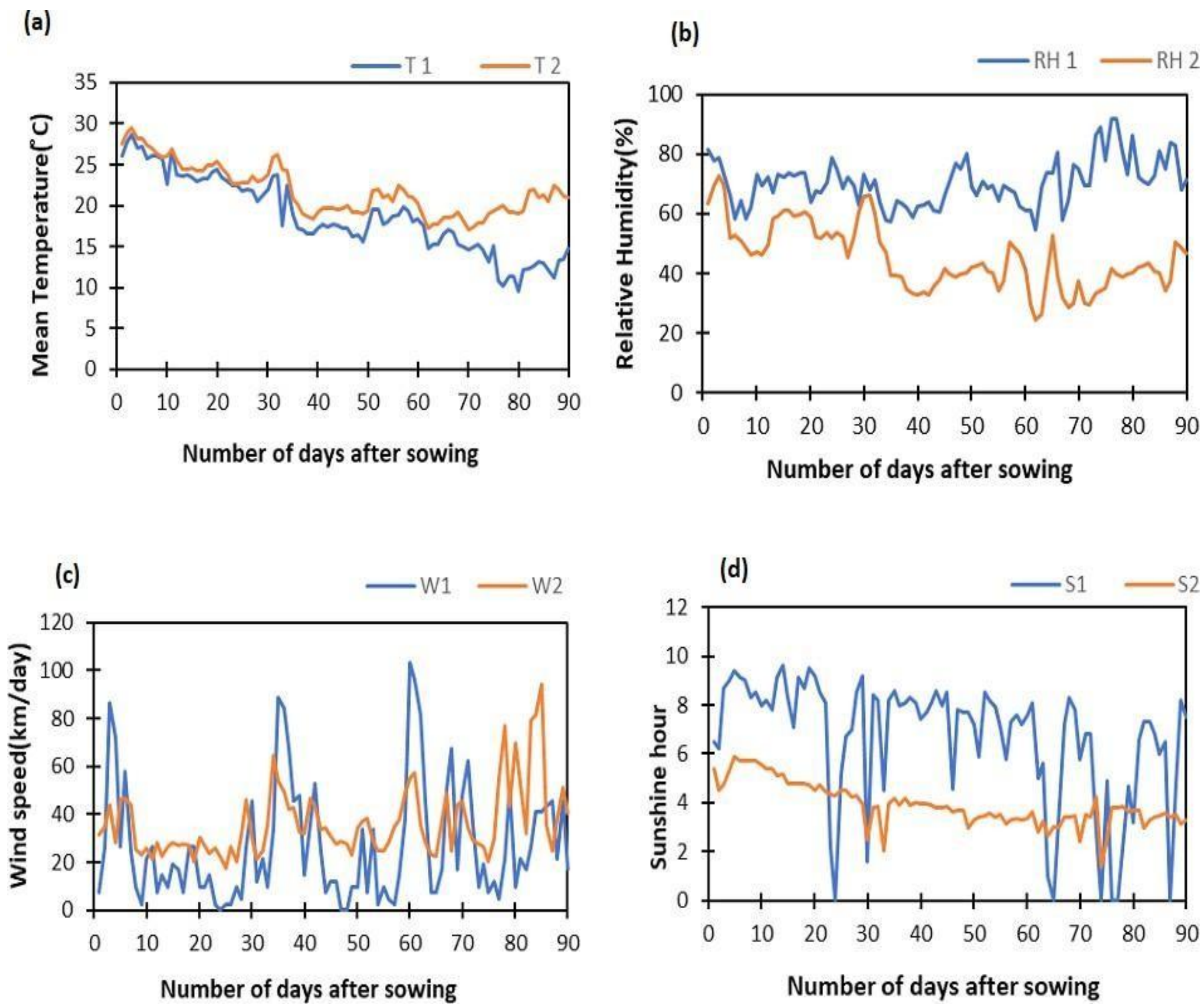


Table.4 Soil hydraulic parameters

Depth (cm)	θr ($cm^3\ cm^{-3}$)	θs ($cm^3\ cm^{-3}$)	α (cm^{-1})	n	Ks (cm d^{-1})
0-5	0.0887	0.4652	0.0181	1.3456	19.13
5-20	0.0912	0.4575	0.0194	1.3031	15.78
20-45	0.0894	0.4364	0.0203	1.2641	11.16
45-50	0.0863	0.4207	0.0205	1.2506	8.74

Fig.3 Temporal variation of simulated and observed soil moisture content at the depth of (a) 5cm, (b) 20cm, (c) 50cm

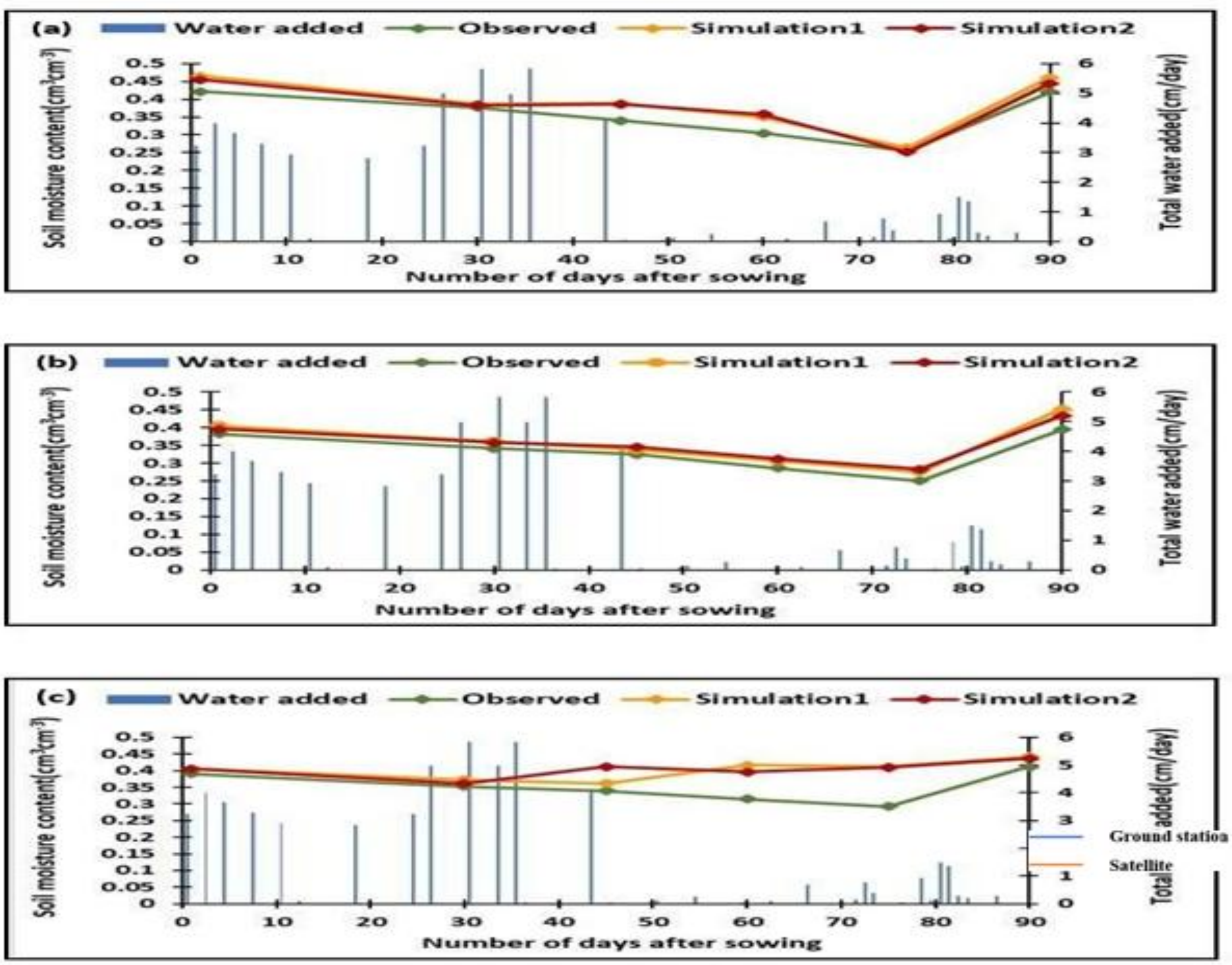


Fig.4 Meteorological parameters, obtained from meteorological station and satellite

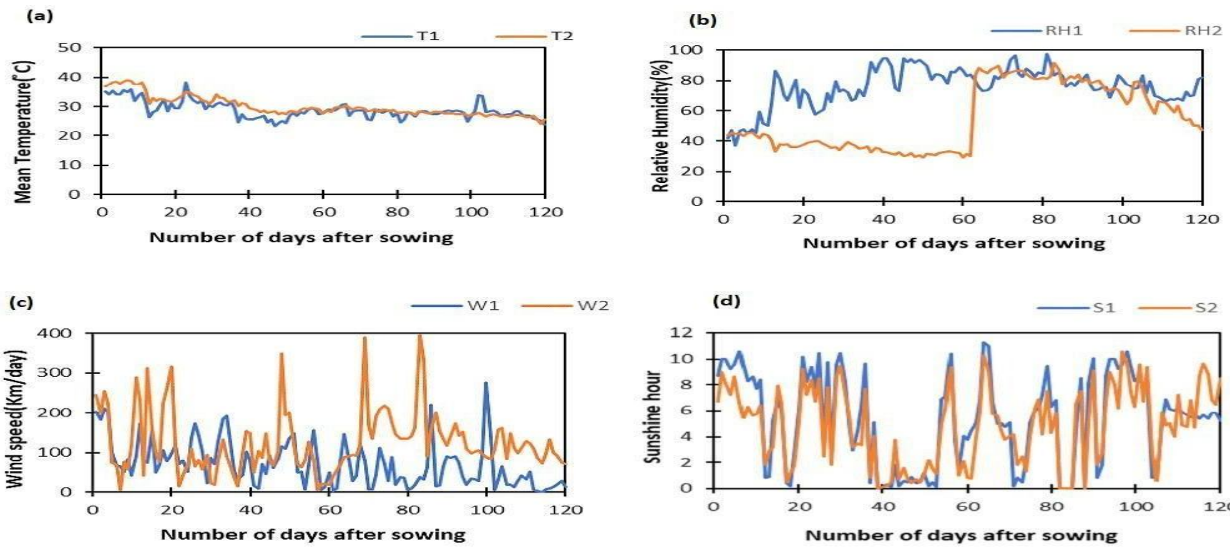


Fig.5 Temporal variation of simulated and observed soil moisture content at the depth of (a) 5cm, (b) 20cm, (c) 50cm

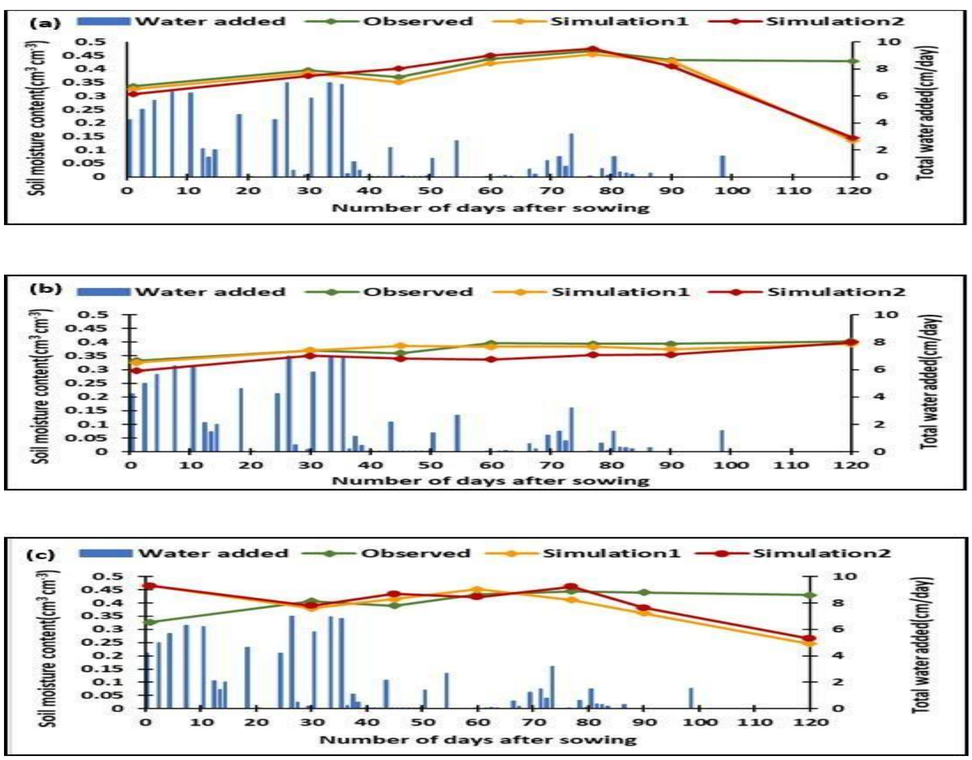


Fig.6 Meteorological parameters, obtained from meteorological station and satellite

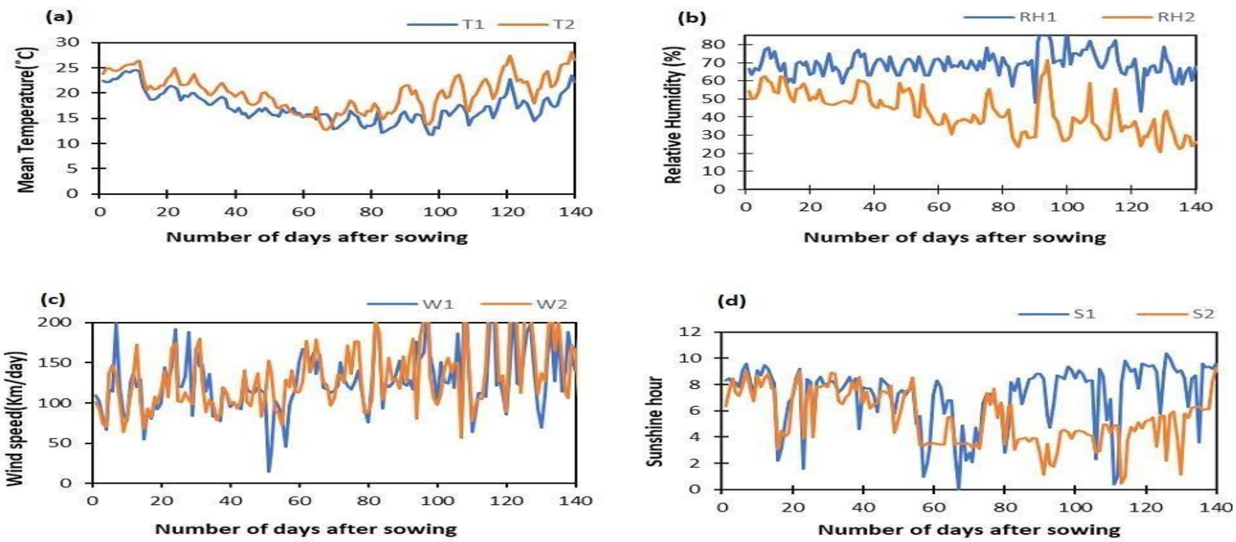


Fig.7 Temporal variation of simulated and observed soil moisture content at the depth of (a) 5cm, (b) 20cm, (c) 50cm

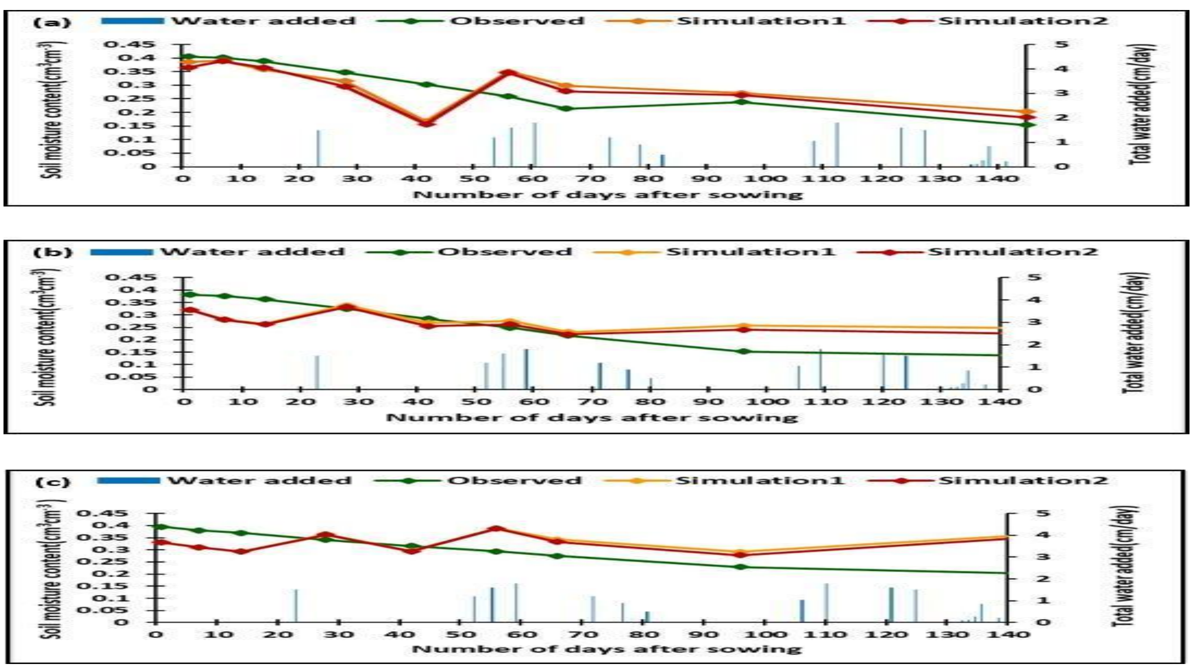


Fig.8 Meteorological parameters, obtained from meteorological station and satellite

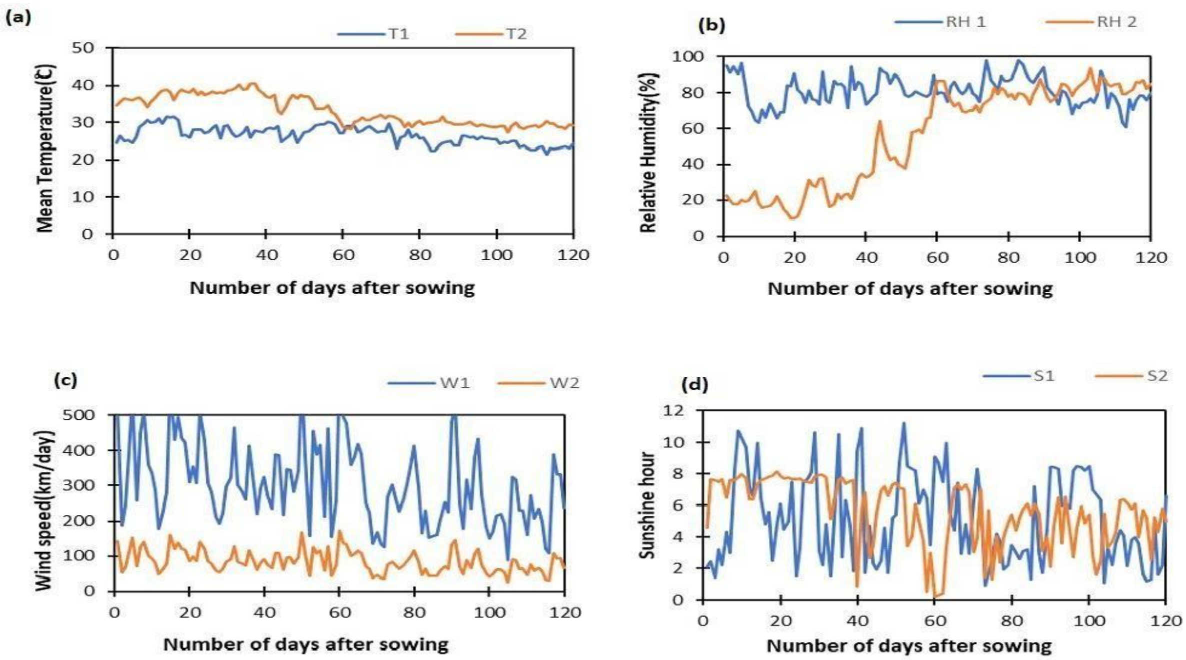
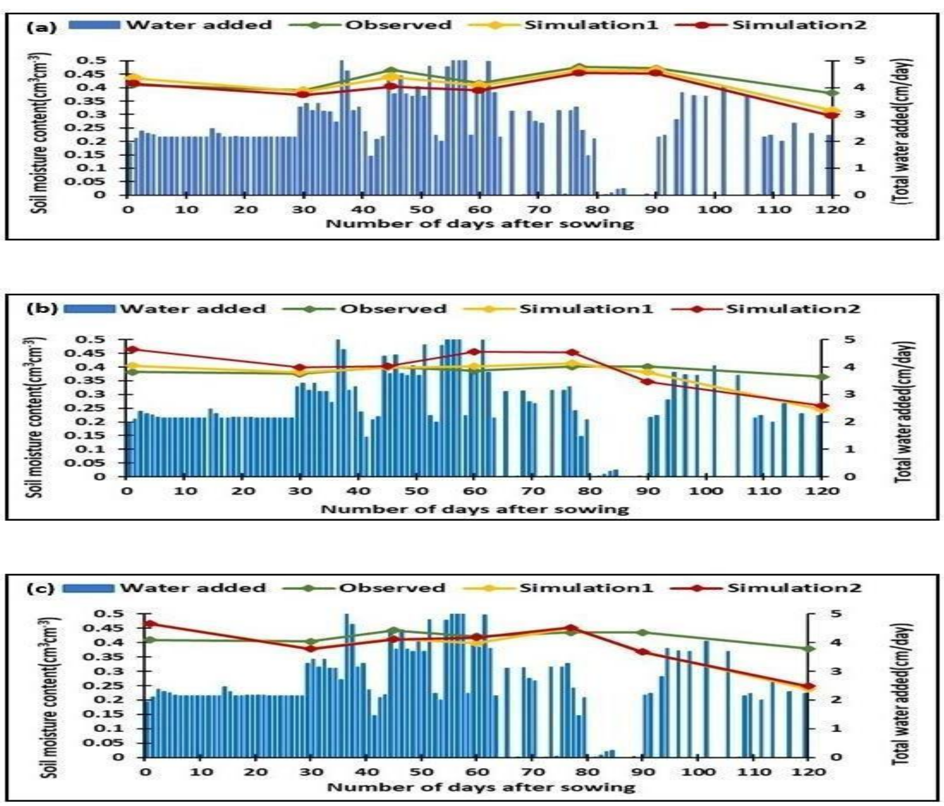


Fig.9 Temporal variation of simulated and observed soil moisture content at the depth of (a) 5cm, (b) 20cm, (c) 50cm



Higher values of deviation were observed after the 90 days of the crop growth at the depth of 5 cm and 50 cm. In the *Kharif* season, the model simulation was found to be satisfactory, as precise irrigation and crop growth data were obtained as well as provided as an input to the model.

Simulation for *Rabi* season

The very next season that falls off is of *Rabi* (25/10/19 - 17/03/2020). During this season the experimental plot was sown by the crop of maize.

Variation of meteorological parameters

Comparison of simulated and observed soil moisture

Figure 3.6 depicts that the model is under estimating the water flow dynamics at all the depths during the initial days of sowing. The underestimation was found to be larger in extent at the depth of 20 cm and 50 cm. Approximately after 30 days of sowing the maize, a great reduction in simulated moisture content was observed at the depth of 5 cm. However, both the modeled simulations were well synchronized.

After 100 days of crop planting, the pattern of stimulation varied greatly at all three depths. Observed soil moisture was seen to be lower in value in comparison to both the simulations. With the duration of the crop increasing in days and moving towards harvesting, the model simulation was not found to be satisfactory at all three depths. The possible reason could be the different root uptake mechanisms of the crop at various crop growth stages. (Chen, Willgoose *et al.*, 2014).

Irrigation data was found to be the most sensitive parameter for STM2. It greatly varies and randomizes the simulations according to the irrigation datasets. This simulation for longer duration crop seemed to be greatly affected by the root uptake mechanism of the adjacent crops which were planted simultaneously during the season. Another flaw of the model could be that it simulates water dynamics on daily basis and distributes the rainfall over a single day hand hence, suppress the surface runoff over the infiltration. More accurate results can be expected if it provides provision of hourly SMC simulation. And it can partition between the infiltration and runoff occurring during the whole simulation period. (Qiao, 2014).

Comparison of simulated and observed soil moisture

During the vegetative growth of the crop, the model was found to be over estimating the water flow at all the depths. This could be due to higher values of the total water or solely irrigation provided to the experimental plot. The values of the soil moisture obtained through simulation 1 were seen higher than the observed moisture content at the depth of 5 cm. However, moisture content values obtained by simulation 2 were seen to be higher at the depth of 20 cm and 50 cm. After 32-35 days of sowing, simulation 1 and 2 showed well coordination to observed soil moisture at the depth of 5 cm and 20 cm. As entering the reproductive phase of the crop growth, simulations 1 and 2 were analyzed to be under estimating at the depth of 5 cm and 50 cm. However, both the simulations were varying from each other at the depth of 20cm. After 90 days of sowing, a great deviation was observed in recorded and modeled simulation in all three depths. High under estimation values were noted during the simulations. The reduction in moisture content can be seen as the irrigation was reduced at this stage of crop growth. This could be expected as a greater difference was observed in the meteorological parameters recorded by satellite and ground stations. The other reason which could be understood from this simulation is that this version does not give information about the macropores flows which results in higher values of net saturated hydraulic conductivity at each soil profile chosen for the simulation purpose. Also, it does not account for the modification in soil distribution at different depths and only considers physical properties for simulation.

Summary

The main purpose of this study was to model the soil moisture dynamics at three different depths of a 50 cm soil profile to understand the varying pattern of vertical movement of water within the soil horizon. STM2 model was used for this experiment. The observed data was gathered from the experimental plot where the soil sensor has been installed.

Hydra probe sensor was installed at the depths of 5 cm, 20 cm, and 50 cm for recording the real-time soil moisture data sets. STM2 requires a vast range of input parameters for simulating the water dynamics at the various depths of a particular soil profile.

Two years of the crop growth period (2018-2020) was selected for the simulation. This span of 2 years was divided into 4 seasons of crop growth including alternative *Rabi* and *Kharif* seasons. Root uptake simulation needs information about certain crop growth data such as LAI, root depth, and plant height. These data were obtained at the significant days of each crop growth.

Soil physical parameters were obtained from direct field measurements in integration with the laboratory methods. Bulk density and percentage of sand silt and clay was obtained by laboratory methods for the determination of soil textural class. All these variables were used to simulate the hydraulic parameters of the soil by putting the value in the inbuilt rosetta. A series of options are present to select the soil textural classes according to the measured parameters.

Crop parameters were also used to simulate the root uptake mechanism. Meteorological parameters were obtained from the two sources. One was generated from a gauging station while the other was downloaded from satellite by providing the geographical coordinates of the place. Two simulations were carried out for each season. Simulation 1 and corresponding the use of the ground station and satellite data simultaneously. Graphical and statistical analysis depicted that model is efficient for simulating the upper layer moisture content and poor values were generated at deeper depths of the soil profile.

The STM2 is a simple and potentially useful tool for modeling soil moisture and temperature conditions to plan agricultural management operation. The quality of STM2 soil moisture estimates varies with soil textural groups. The model worked best with the Sandy and Loamy soil textural groups, which had the lowest RMSE values and the highest d indices. Its moisture estimates were only moderately good for the Clayey soil, and they were unacceptable for the Gravelly soil. Addition of data on the percentage of coarse fragments in the soil or PTFs based on gravelly soil types would probably improve soil moisture prediction. The quality of soil temperature estimates was not as dependent on the soil textural group. In fact, the performance of the model was better for temperature than moisture at all soil types. The quality of soil moisture estimates also generally decreased with increasing depth. Weeds germinate at shallow depths; thus, the model was not designed to estimate conditions at greater depths.

Crop phenology had an impact on the performance of STM2 soil moisture estimates. Thus, the best soil moisture estimates were generated during the seeding to emergence and flowering to senescence periods, characterized by relatively low ET activity, which is not considered by STM2. This suggests that STM2 could be highly useful only at the beginning of a growing season, when efforts to control weed germination are underway.

A model that accounted for plant development might be more appropriate during the period of higher water demand for ET. Temperature estimates were accurate at any time during the corn growing season. The sensitivity analysis revealed that primary soil properties have an impact on soil moisture predictions according to soil textural groups. Among the secondary soil properties derived from PTFs, bulk density and saturated hydraulic conductivity had the greatest impact on soil moisture.

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How to cite this article:

Bhavna Singh, A. K. Nema and Prashant K. Srivastava. 2023. Estimation of Soil Temperature and Moisture Using STM Model in Varanasi District of Uttar Pradesh, India. *Int.J.Curr.Microbiol.App.Sci.* 12(07): 119-132. **doi:** https://doi.org/10.20546/ijcmas.2023.1207.014