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Artificial Intelligence and Digital Application in Soil Science : Potential Options for Sustainable Soil Management in Future

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ABSTRACT

Soil supports plant growth by supplying nutrients and water and thus plays a key role in agricultural production system. Therefore, sustainable management of soil resources is very important to meet the food production targets. Soil nutrient statuses are generally monitored on regular basis to apply additional nutrient requirement for plant growth through manures and fertilizers. Similarly, soil hydraulic properties e.g. hydraulic conductivity, water retention etc are to be characterized in order to apply right amount of irrigation water at right time. Conventionally, soils are characterized through field sampling followed by their laboratory analysis. However, considering the spatial variation of soil properties and time required to measure these properties in laboratory, it if often found difficult to collect multiple samples from field and then to determine soil properties in laboratory. With the advancement in digital technology specifically the artificial intelligence and machine learning tools, there is huge scope to apply these technologies to assess soil properties in field in a quick time. Here, we discusses few potential options of artificial intelligence and digital technology to apply in soil science. Digital camera can be used to prepare digital soil library and then applying machine learning tools on the large database on digital photographs may be possible to relate soil properties with colour. Machine learning tools e.g. random forest regression, support vector machines, regression tree etc. can be applied to prepare digital soil maps using legacy soil data after considering the 'scorpan' factors of soil formation. The available information of soil resources as well as the information generated through machine learning tools can be made available to stakeholders through soil information system in different platforms e.g. android application in smart phones, web GIS in desktops etc. Further, handheld devices may be developed to quickly measure soil properties in field. Therefore these technologies have huge potentials in agriculture and coworking robots (cobots) is a futuristic option.

Key words : Artificial Intelligence; Machine Learning; Digital Soil Mapping; Soil Information System; Handheld Device; Digital Camera

Introduction

Soil plays a key role in agricultural production system by supporting plant growth through supplying required nutrients and water as well as in hydrological cycle by partitioning

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rainwater into runoff and infiltration. Therefore knowledge on soil properties helps in better management of both soil and water resources for sustainable crop production. However, soils vary largely in space and therefore characterizing it for a particular landscape with a set of soil parameters is a difficult task. Therefore, a homogeneous zoneis often considered in the field with an assumption of having similar soil properties within the unit for better soil management. Characterizing soil over a spatial scale through maps are the best option for precision farming and digital soil mapping (DSM) approach is more appropriate for this purpose. The DSM approach considers 'clorpt' factors of soil formation theory proposed by Dokuchaev (1883) and Jenny (1941), which was later on modified as 'scorpan' factors (McBratney *et al.*, 2003). Environmental, topographical and other anthropogenic factors have been considered in DSM approach while modelling soil properties of interest over a spatial scale. Thus, the estimates of soil properties through DSM approach are expected to be more accurate. However, there is need to handle large soil database in the DSM approach e.g. legacy soil data along with digital data on earth features, climatic variables, topographical attributes etc. and analyse them. Hyperspectral soil signatures and digital sensors in recent times have added the strength of DSM approachand to improve the accuracy of digital soil products further. With the advancement of digital technologies, specifically in machine learning algorithms there is possibility to develop mathematical relationship between complex soil properties and several environmental and climatic variables(Murase, 2000, Banerjee *et al.*, 2018, Jha *et al.*, 2019). Even, there is possibility to develop intelligence system similar to human brain, which can produce the same output after learning the previous dataset on input and output for a soil system as a human being does. Machine learning tools are appropriate to analyse and model large soil database.Different machine learning tools are now available to identify the trend in large legacy soil database consisting data on several inter dependent soil properties. Few common machine learning tools are support vector machine (SVM), random forest regression (RF), artificial neural network (ANN), fuzzy logic (FL), decision tree (DT), deep learning (DL) etc. Thus, it becomes easy for a machine or device to learninput-output relationship in a better way. Therefore, artificial intelligence (AI) has been gaining popularity in recent times and few common applications of AI are speech recognition, smart home systems, robotic medical surgery etc. Another recent development in computer science is 'internet of things' (IOT), which is a network of several communicating devices. These communicating devices may be computer, notepad, smartphone, Wi-Fi router, laptop etc. In the IOT system, chain of inputs and outputs have been made to take a final decision and each operation is fully based on automation.

Digital soil mapping have been gained importance in different parts of the world during last two decades (McBratney *et al.*, 2003~ Lagacherie *et al.*, 2006~ Behrens *et al.*, 2006~ Grunwald, 2009~ Sanchez *et al.*, 2009; Santra *et al.*, 2017; Dharamurajan *et al.*, 2019). To get quantitative answers on role of soil in carbon sequestration and its impact on biomassproduction and human health, GlobalSoilMap.Net project has been implemented by FAO and UNESCO in the year 2006. World Soil informationCentre (ISRIC, Netherland) have been working on several projects on digital soil mapping e.g. Global Soil Information Facilities (GSIF), AfricaSoil Information Service (AfSIS), World Inventory of Soil Emission Potentials (WISE), Soil and Terrain Database (SOTER) etc. Apart fromthese International programmes, several countries have initiated their own digital soil mapping programmes e.g. DIGISOL in Europe, OzDSM inAustralia, NCSS digital soil mapping programme of USA, SISINTA in Argentina, SISLAC in Latin America etc. In India, digital soil mapping has been initiated long ago by Agarwal and Gupta, (1998) followed by several researchers during last two decades (Das, 2007~ Santra *et al.*, 2008~ Kamble and Aggrawal, 2011, Santra *et al.*, 2012a~ Santra *et al.*, 2012b~ Chatterjee *et al.*, 2015, Singh *et al.*, 2016~ Santra *et al.*, 2017, Dharamurajan *et al.*, 2019). A comprehensive review on methodology of digital soil mapping along with present status and future requirements have been reported by Santra *et al.* (2017). All these digital soil mapping programmes were based on legacy soil data availablefrom different surveying efforts. Since, these legacy databases had been generated across different years and with different categories of both quantitative and qualitative data, there is need to apply machine learning tools to understand these data and to build suitable models.

Rapidly measurable soil spectral signatures may help to develop algorithms for estimation of soil properties (Shepherd and Walsh, 2002~ Brown *et al.*, 2006~ BenDor*et al.*, 2009~ ViscaraRossel *et al.*, 2016~ Katuwal *et al.*, 2017). Further, the developed algorithms may be translated to remote sensing platforms, low flying aircrafts, and even to drones to prepare map of soil properties in a quick time. A quick scan of geocoded soil samples can even estimate soil properties using the spectra based algorithms, however, large soil spectral library representing different soil types in India may be required for this purpose. Efforts have been made in India for soil spectral library generation (NBSS & LUP, 2005~ Saxena *et al.*, 2003~ Srivastava *et al.*, 2004~ Singh *et al.*, 2014), however, there is need to strengthen the effort. Moreover, few soilspectrabased algorithms have also been developed for rapid assessment of soil properties. For example, (i) Santra *et al.* (2009)estimated soil hydraulic properties using proximal spectral reflectance,(ii) Gulfo *et al.* (2012) assessed soil moisture content using hyperspectral reflectance, (iii) Divya *et al.* (2014) characterized soil texture usinghyperspectral reflectance, (iv) Kaduputiya *et al.* (2010) assessed soil nutrient contents using diffused reflectance spectra etc. Apart fromthese, reflectance spectroscopy has been successfully applied to estimate other soil properties in different states of India e.g., West Bengal, Rajasthan, Karnataka etc.(Sharathjith *et al.*, 2014~ Santra *et al.*, 2015; Mohanty *et al.*, 2016~ Gupta *et al.*, 2016~ Chakraborty *et al.*, 2017). A detailed review on current status and future prospects of hyperspectral signature based soil resource assessment has been reported by Das *et al.* (2015). In spite of several efforts and developments in digital applications as mentioned above, there is need for further development and applications in field in order to sustainable soil management for future. Even to attract the youth of the country in agriculture, such digital application may be more appropriate. However, to apply digital technology in highly scattered land units of India following different land management practices is a challenging task. Soil health card mission of the country has been launched with the enthusiastic aim to recommend fertilizers and other input resources in the farmer's field based on the soil test reports. With the advancement of digital technologies as mentioned above, the aim is achievable, provided soil information systemsin the country are developed and made it available in digital platform. Even, sensor-based techniques need to be developed for in-situ characterization of soil in the field and communicating the output to IOT platform to take a decision on nutrient and water application in soil. Therefore, the present paper discusses few potential options for sustainable soil management in future.

2. Materials and methods

2.1. Digital soil library

Digital photographs of soil samples collected from arid western Rajasthan were recorded at laboratory using Nikon camera (Model: Coolpix S6500). Two standard D65 white lamps were used to illuminate soil samples as to represent day light illuminance.The camera was placed overa GI sheet platform at a height of 45 cm above soil samples.Photograph of each sample was taken using timer function of camera to avoid disturbances while snapping pictures. Further, the digital image of each sample was processed and an image frame of 100 ´ 100 pixel was extracted for further analysis. Digital image processing of the selected image was carried out using 'imager' package of R (Bartheleme *et al.*, 2018 and R Core Team, 2013). Colour parameters of RGB colour space model for pixels of the sample image was retrieved and mean R, G, and B value of the whole sample image was calculated. Standard deviations of R, G, and B values were also calculated to identify the noisy image. Images with standard deviation greater than 10% of its mean value for any of the three colour parameters is marked as noisy image. For noisy image, the step of extraction of 100 ´ 100 pixel sample image was repeated and the image was further analysed to finally select a noise free image. Furthermore, soil colour indices were calculated from the mean R, G and B value for each sample image using the formula as described in Levin *et al.* (2005).

Redness index (RI) = $[(R^2 + G^2 + B^2)/3]^{0.5}$

Saturation index (SI) = $(R-B)/(R+B)$

Hue index (HI) = $(2*R-G-B)/(G-B)$

Coloration index (C) = $(R-G)/(R+G)$

Redness index, RI = $R^2/(G*B^3)$

Exploratory analysis of these colour indices and its relation with basic soil properties was further carried out. The main purpose of the analysis was to identify soil properties, which can be predicted using digital photographs and further to develop a digital photograph based algorithm for rapidly estimating the soil property.

2.2. Digital photographs and estimations of soil moisture

Digital photographs of soil samples with different moisture content was captured and further analysed to estimate soil moisture content using digital photographs. The methodology to capture the image using digital camera and further analysis of the captured digital image using 'imager' package of R is the same as mentioned above. For simulating different soil moisture contents in the laboratory, following stepwise methodology was followed. A known quantity of air dry soil after passing through 2 mm seive was taken in a petri dishes with a thickness of about 2 cm. The soil sample was then saturated by adding a known quantity of water to attain an approximate gravimetric moisture content of 25%. Actual moisture content of the saturated soil sample was determined by weighing the soil sample. Photographs of the saturated soil was then captured using Nikon camera. After capturing the photograph of the saturated soil sample, it was kept inside an oven to dry it in a sequential time steps. During drying phase, gravimetric moisture contentwas determinedat each time step and image of the sample at that particular moisture content was captured. The procedure was followed till soil moistue content was driedto about 2-3% on gravimetric basis. The procedure was also followed for different soil types found in western Rajasthan. Finally, soil regression based models have been developed to estimate soil moisture content from color parameters of the soil samples.

2.3. Hyper spectral signature based estimation of soil property

Spectral reflectance of 19 selected soil samples with varying EC and pH from the Narmada canal command area at Sanchore was measured using spectroradiometer (Model: SVC, HR1024). Spectral readings of each soil sample were recorded in duplicate and average spectral reflectance at 1 nm interval in the spectral wavelength region 350-2500 nm was further processed. Exploratory analysis of soil reflectance spectra and its relation with soil pH and EC was carried out. Correlation coefficient of soil pH and EC with soil spectral reflectance at each wavelength was calculated. Plot of wavelength versus correlation coefficient was made to identify the specific wavelength region of importance to estimate soil pH and EC.

2.4. Random forest (RF) regression based digital soil mapping

RF regression consists of an ensemble of randomized classification and regression trees (CART) (Breiman, 2001). Several number of trees are generated within the RF regression based algorithm, which are finally aggregated to give one single output using the average of the individual tree outputs. RF depends on three user defined parameters: (i) the number of trees (ntree) in the forest, (ii) the minimum number of data points in each terminal node (nodesize), and (iii) the number of features tried at each node (mtry). Here, an example of RF regression for preparing digital soil map of sand content in arid western India is presented, which has been described in detail in Santra *et al.* (2017). Covariates on soil map, terrain attributes and bioclimatic variables were used for RF prediction of sand content from a legacy soil data of the region. In the RF regression algorithm adopted in this study, ntree was used as 1000, nodesizewas used as 5 and mtrywas used as one third of the total number of predictors. RF regression was carried out using 'radomForest' package of R (R Core Team, 2013 and Breiman *et al.*, 2018).

2.5. Soil information system

Soil information system (SIS) plays a key role to cater the needs of stakeholders e.g. farmers, policy makers, researchers etc. In this paper, two type of SISs are discussed. The first one is a software, named as 'CAZRI soil moisture calculator'. The software was based on the pedotransfer functions (PTFs) for estimating soil water content at field capacity (FC) and permanent wilting point (PWP) using basic soil proerties e.g. sand content, silt content, clay content, and soil organic carbon (SOC) content. The PTFs are multiple linear regression based model in which sand, silt, clay and SOC can be used as input to obtain soil moisture content at FC and PWP as output. The PTFs were developed using legacy soil data of arid western India, details of which may be found in Santra *et al.* (2018). The software was deveoped using Microsoft visual basic 6.0 programming language. The similar information was further developed in to a second SIS, which is a webGIS application of the PTFs. In the second SIS, the PTF based caculator has been developed using PHP programming language.The flow chart of the SIS is given in Fig. 1.

The input data of sand, silt, clay and SOC in the PHP based calculator has to be assigned after extracting its value from the respective digital soil map of arid western India through postgreSQL, which is also known as 'postgress' and is a free and open-source relational database management system. The geographical location of any place within arid western India is obtained using opensource map of Google in Java script after registering with an application programming interface (API) key. The geographical location is then passed to postgreSQL query to get the value of sand, silt, clay and SOC for that partiular location. The whole SIS has been developed using Apache HTTP server. Therefore, the second SIS is enabled to provide information of basic soil properties of any location within arid western India. Further, it has also the feature to calculate soil water retention at FC and PWP based on the iformation on basic soil properties. Provisions are also available in the SIS to calculate other soil hydraulic properties using the inforation on basic soil properties. Latsly, an android application of soil information system has been developed by which information on soil archives in a soil testing laboratory can be accessed through smartphone.

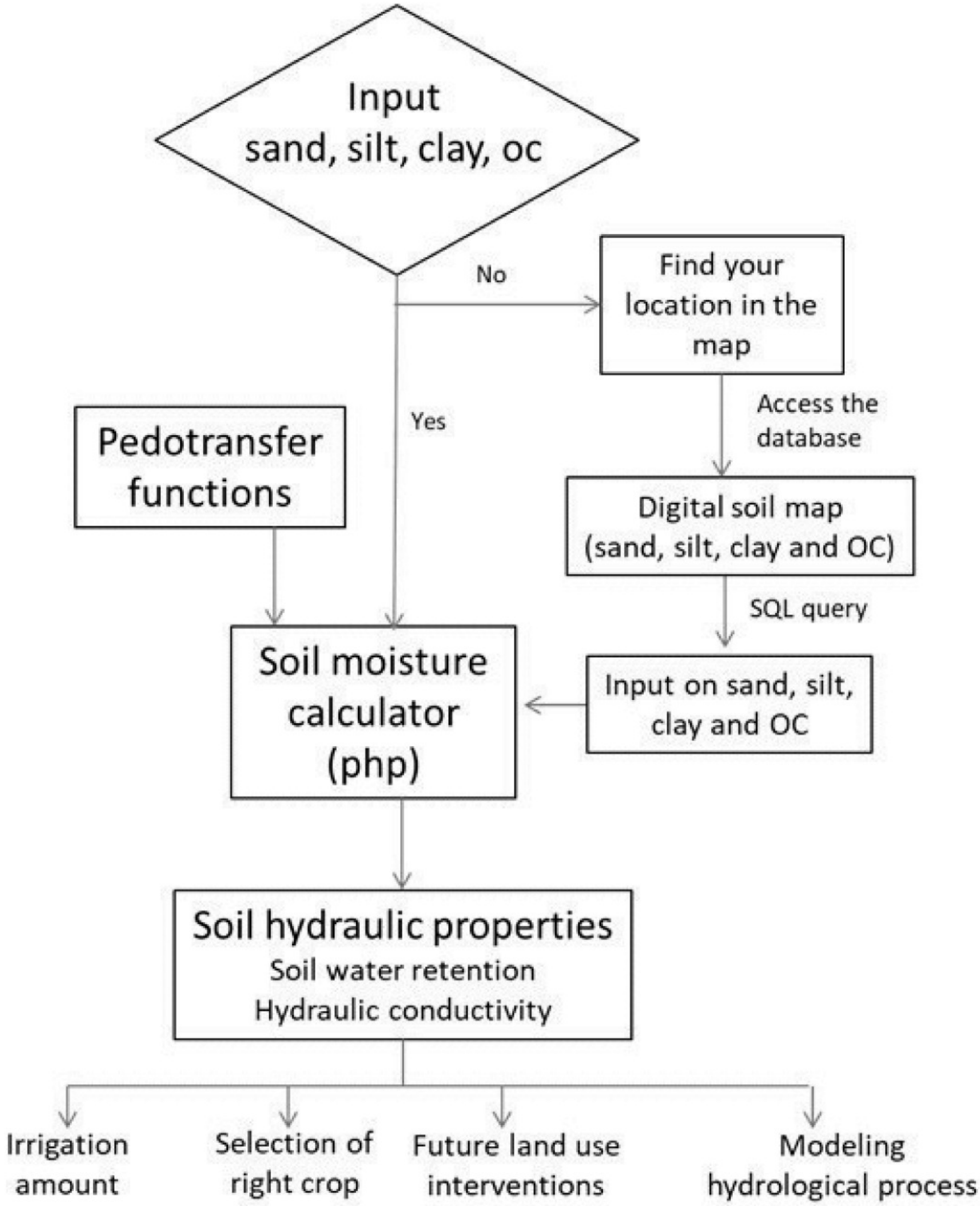

Fig. 1. Flowchart of soil information system

2.6. Hardware for estimation of critical soil water content

Further, the PTF based SIS was developed in to a handheld device. In the device, alphanumeric keys are provided to enter the input of sand, silt and clay. Liquid crystal display (LCD) is provided in the device to visualise the inputs. Available PTF model can be selected in the device using LCD screen. Finally the output of the device is calculated using a printed circuit board (PCB), in which PTF models have been coded. Provision of battery back up and charging facility of the handheld device have also been given. The handheld device can be turned on/off using a switch.

3. Results and discussion

3.1. Digital soil library of western Rajasthan

Digital soil library of 100 soil samples covering different soils from western Rajasthan are given in Fig. 2.From the figure, it has been seen that its colour varies from yellow to red. Parent material generally dictates soil colour. Apart from parent material, soil organic matter influence the darkness of the soil colour. Whereas saline soil is expected to increase the lightness of the soil colour. Likewise, several other soil parameters influence soil colour. It is to be noted here that soil colour is conventionally defined through Munsell colour chart that is based on Munsell colour system. In the Munsell colour system, colour is defined by three parameters: hue representing major colour, value represents lightness ranging from 0 to 10, and chroma represents the purity of the colour with a range from 0 to 20. For example, munshell notation of 5YR 5/6 represents soil colour with a hue of yellowish red (YR), value of 5, and a chroma of 6. One disadvantage of Munsell colour value is that it is qualitative data and hence often becomes difficult to analyse. However, with the advancement of digital technology, the soil colour can be recorded using digital photographs in RGB colour space model, which can be converted to Munsell colour space model, CIELAB colour space model etc. Likewise, Munsell colour values in legacy soil data can be converted to digital value of RGB colour space model e..g. using munsell_to_rgb command of soil profile package in R.

Soil properties along with their colour values and colour indices are given in Table 1. Colour parameters R, G and B showed a large variation across soil samples which are about 7.39%, 11.34%, and 16.6% of their mean values. It shows large potential to use soil colour as a surrogate to estimate few soil properties, specifically those which directly influences soil colour. Apart from it, there are several machine learning tools (e.g. deep learning) now available which can analyse digital colour photographs in RGB colour model to get information on spectral reflectance in narrow spectral bands in the visible wavelength spectrum. There is also possibility to calculate the parameters of other standard colour space model from RGB colour space model, which may infer soil properties in a better way than the RGB colour parameters.

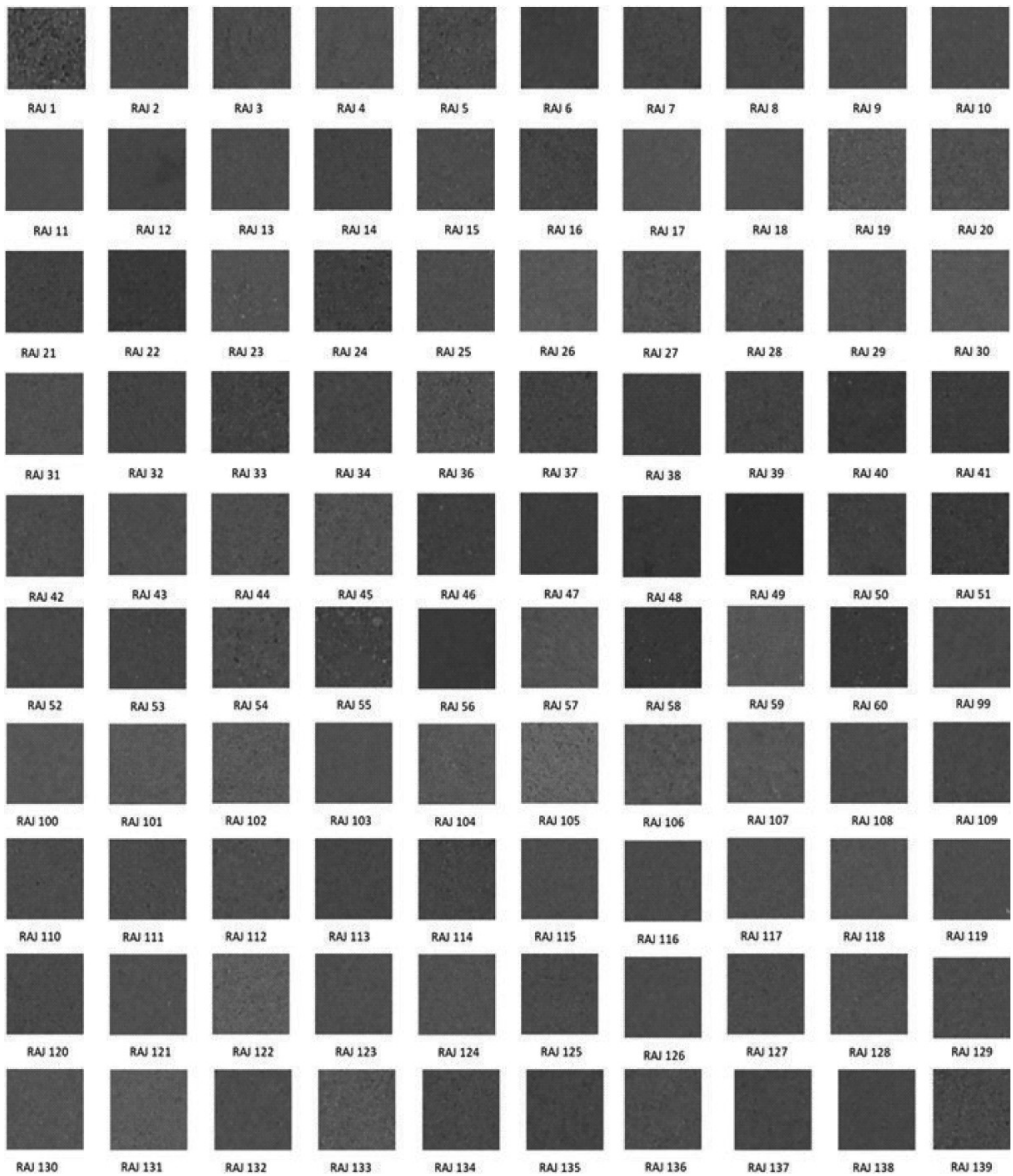

Fig. 2. Digital photographs of soil samples in RGB colour space model representing different soil types of western Rajasthan, India

Table 1. Soil properties, colour values and colour indices of soil samples collected from Jodhpur, Jaisalmer, Barmer and Churu district of Rajasthan

Soil colour values and indices	Minimum	Maximum	Average	Standard deviation
Sand (%)	49.00	98.00	89.02	9.63
Silt (%)	0.05	34.35	4.95	6.20
Clay (%)	0.00	23.40	6.03	4.17
Organic carbon (%)	0.01	0.74	0.18	0.14
Total carbon (%)	0.09	2.41	0.51	0.42
pH	7.02	8.73	7.93	0.29
EC (mS cm^{-1})	5.61	805.00	199.36	133.54
R	101.88	153.97	131.29	9.69
G	61.07	128.68	103.81	11.74
B	31.19	82.38	57.54	9.59
Brightness index, BI	73.05	124.67	102.29	9.32
Saturation index, SI	0.26	0.55	0.39	0.05
Hue index, HI	1.72	4.03	2.21	0.41
Coloration index, C	0.06	0.27	0.12	0.04
Redness index, RI	1.3´10^{-4}	15.9´10^{-4}	3.1´10^{-4}	1.8´10^{-4}

3.2. Digital photographs to estimate soil moisture

Digital photographs of soil samples with different moisture content are shown in Fig. 3. Here, photographs of four major soil types representing sand dunes from Jaisalmer, soils under shelterbelt plantation of mopane (*Colophospermum mopane*) at Chandan and soils from agricultural land at Osian and Jodhpur are shown. It is clear from the pictures that inherent parent material of the location has a major role in soil colour. However, there is increase in darkness of soil colour with increase in soil moisture content.

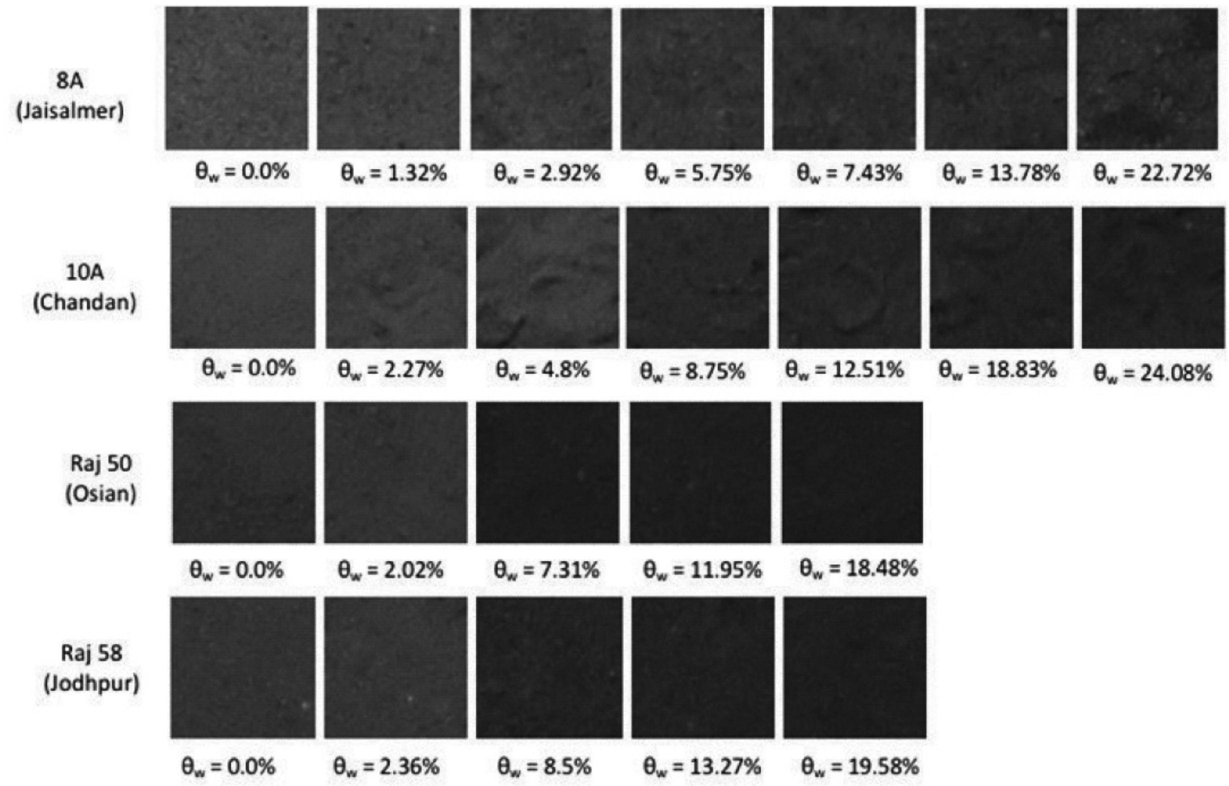

Fig. 3. Digital photographs of soil samples from western Rajasthan with different soil moisture content

Relationship between soil moisture content and soil colour parameters are shown in Fig. 4. Here, it is noted that colour of any object is defined by digital number (DN) ranging from 0 to 255 for each of the three colour parameters R, G and B in RGB colour space model. A DN value of 255 indicates maximum possible value of a colour parameter whereas a DN value of 0 indicates minimum possible value. True colour of an image is visualised as mixing of these three primary colours and digital photographs captured by a camera is generally visualised in RGB colour space model. A colour pixel with [R, G, B] matrix value of [0, 0, 0] is pure black whereas the matrix with values of [255, 255, 255] is pure white. From Fig. 4, it is observed that DN value of R ranges between 120 and 140 in dry condition, which was reduced to about 80-100 on near saturated moisture content. Similarly, the DN values for G and B were also reduced from its dry condition to near saturated state. This indicates that there is possibility to estimate soil moisture content by reading the R, G, nd B value through a digital camera or a smartphone camera. On further building the relationship between soil colour parameters and soil moisture content, we observed good coefficient of determination (R^2) for linear model. For example, the linear model between DN value of R and soil moisture content was found 0.67. The linear models of G and B with soil moistire content resulted in comparatively lower R^2 value than of R with soil moisture content and these are 0.51 and 0.43, respectively. Thus, if the digital soil library of different soil types with different soil moisture is preapared, it is possible to develop a robus model to estimate soil moisture. Further, a suitable android based application can be developed which may help farmers to estimate soil moisture in the field using smartphone and then to apply irrigation water judiciously.

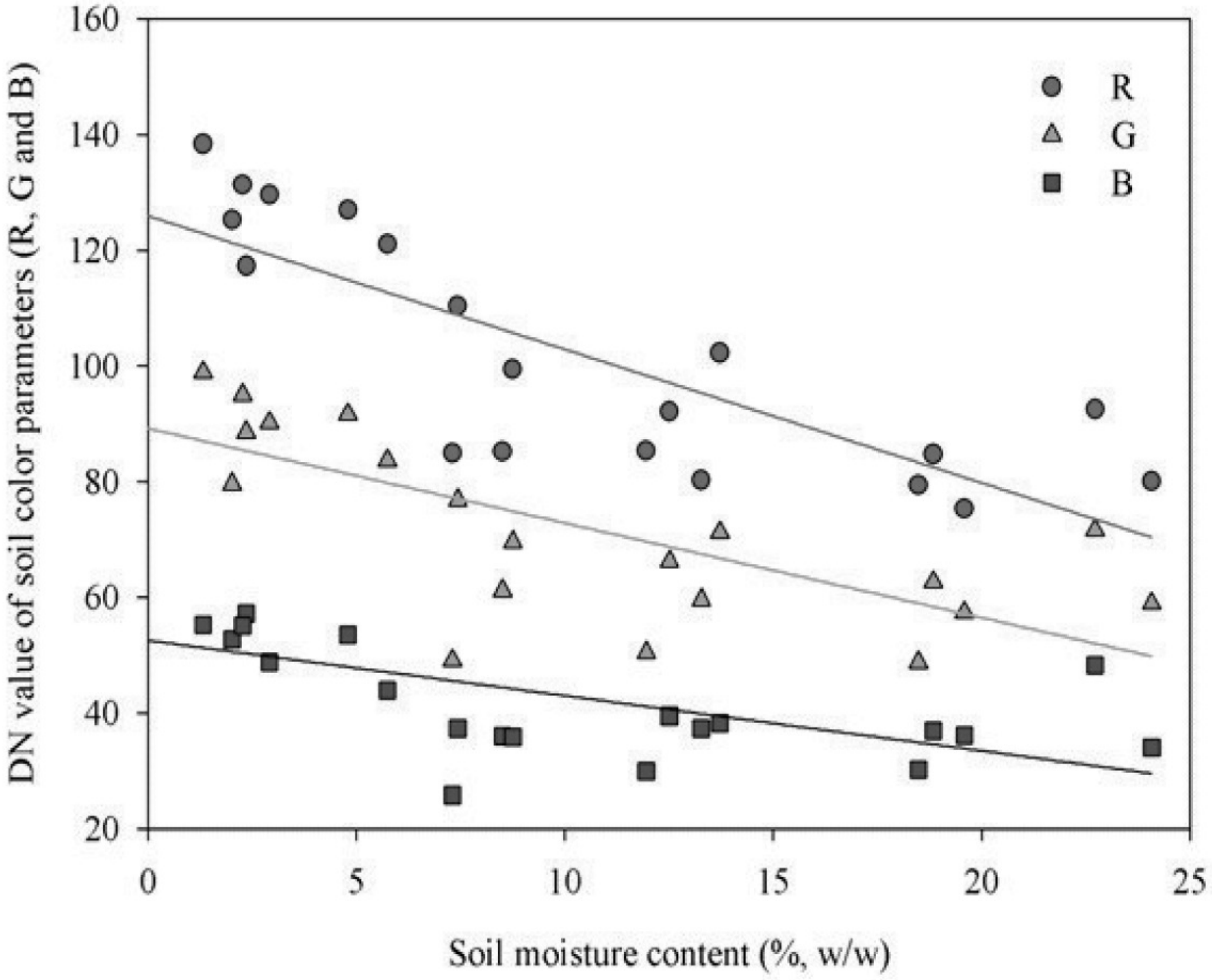

Fig. 4. Relationship between soil moisture and digital color parameters R, G and B

3.3. Hyperspectral signature for assessing soil salinity

Spectra of three selected soils with EC values of 0.27 dS m^{-1}, 7.44 dS m^{-1} and 39.3 dS m^{-1} are presented in Fig. 2. It has been observed that spectral brightness was higher for soils with high EC value as compared to low EC value. Correlation coefficients between reflectance at each wavelength and corresponding soil EC are plotted in Fig. 5. It has been observed that correlation coefficient was about 0.6-0.7 at wavelength region 350-500 nm. At higher wavelengths (>950 mm) correlation coefficient is low but positive. Similarly, correlation plot between pH and reflectance shows maximum correlation coefficient of 0.40 at wavelength region of 350-500 nm. Beyond 950 nm wavelength, correlation between pH and reflectance is negative and varies from -0.1 to -0.2.

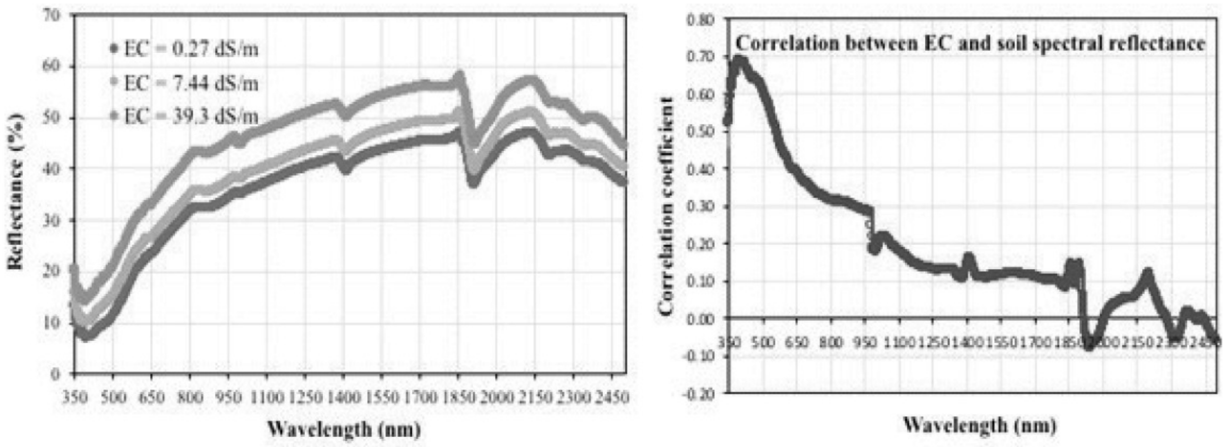

Fig. 5. Spectral reflectance of soil properties in 350-2500 nm wavelength region with different EC values and the correlation coefficient between reflectance and EC

3.4. Random forest regression based digital soil mapping

Stepwise multiple regression algorithms were first used to select the important covariates from a list of covariates e.g. soil map, terrain attributes, bioclimatic variables etc and further these identified covariates were used to develop RF regression based trend model. Predicted sand content by RF trend model showed a close proximity with observed sand content (Fig. 6). In addition to covariates used in this study, further inclusion of other covariate information e.g. Landsat band reflectance, composite vegetation indices, land use/land cover map, geology map etc. may further improve the RF regression based trend estimation of sand content.

Predicted maps on sand content in arid western India using RF regression model are presented in Fig. 7. Higher sand content in surface layers than subsurface layers were observed in the maps. The major advantage of RF regression based map is that use of a finer resolution covariate map leads to fine resolution digital soil mapping products. Thus, with limited and sparsely available legacy soil data from which it is difficult to determine a good semivariogram model, RF trend model using environmental covariates may provide a solution to develop digital soil products.

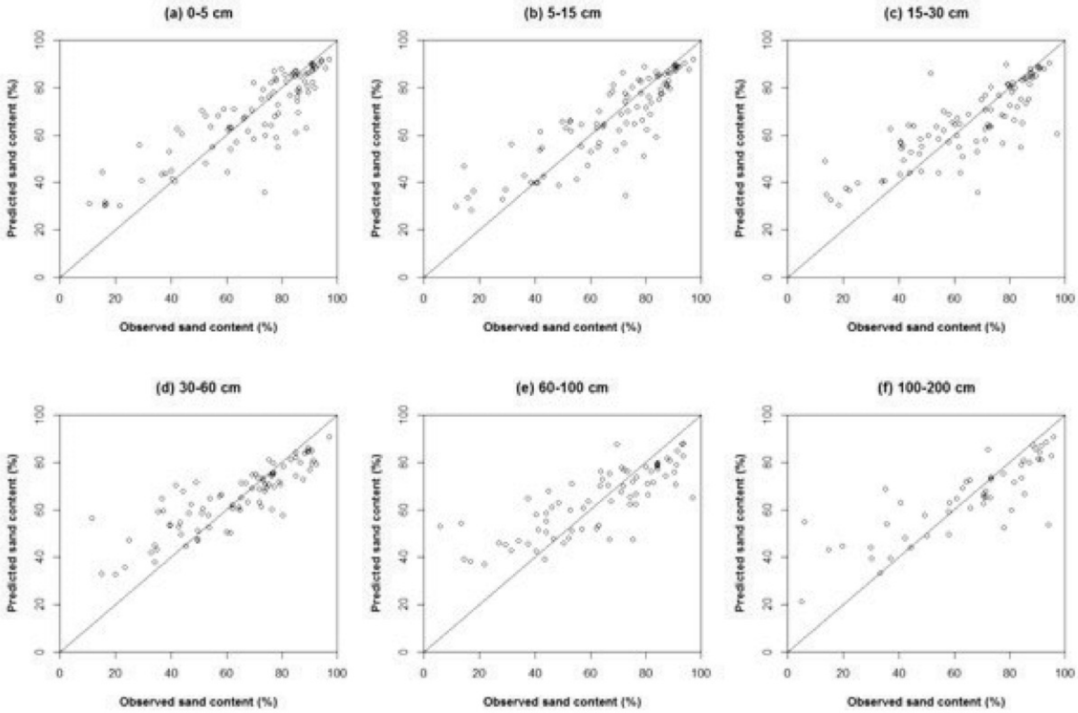

Fig. 6. Observed vs predicted sand content through random forest regression using covariates on soil suborder association map, terrain attributes and bioclimatic variables

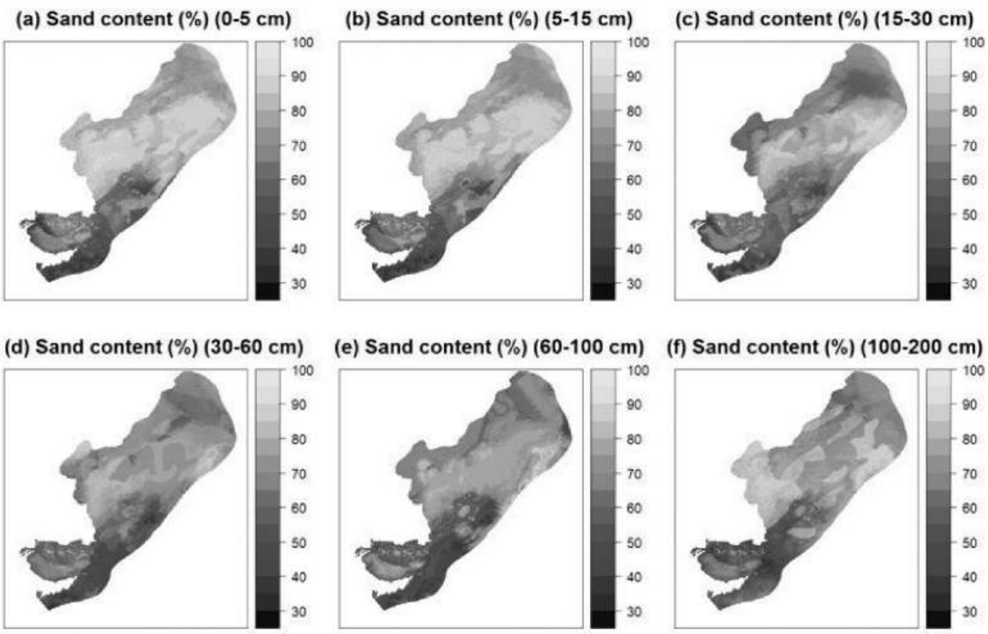

Fig. 7. Predicted sand content through random forest regression using covariates on soil suborder association map, terrain attributes and bioclimatic variables; (a) 0-5 cm, (b) 5-15 cm, (c) 15-30 cm, (d) 30-60 cm and

3.5. Soil information system

3.5.1. *CAZRI soil moisture calculator*

Screenshot of CAZRI soil moisture calculator is given in Fig. 8, which is also available in the website http://www.cazri.res.in/soil-moisture-calc.php. The calculator estimates the FC and PWP water content using the arid zone specific PTFs developed by us using the soil database from arid western India. Using the calculator, one can also use other established PTF models developed elsewhere in the world. The calculator may be helpful by in estimating right amount of water to be applied in field. For example, an input of sand, silt and clay content of 87%, 8% and 5%, respectively has resulted in to a soil water content at FC and PWP of 7.07% (w/w) and 1.92% (w/w), respectively. Further, the FC and PWP moisture content have been converted to available water capacity (AWC) of 11.50 mm in 0-15 cm soil layer. These information may be useful to farmer to take decision on applying right amount and at right time.

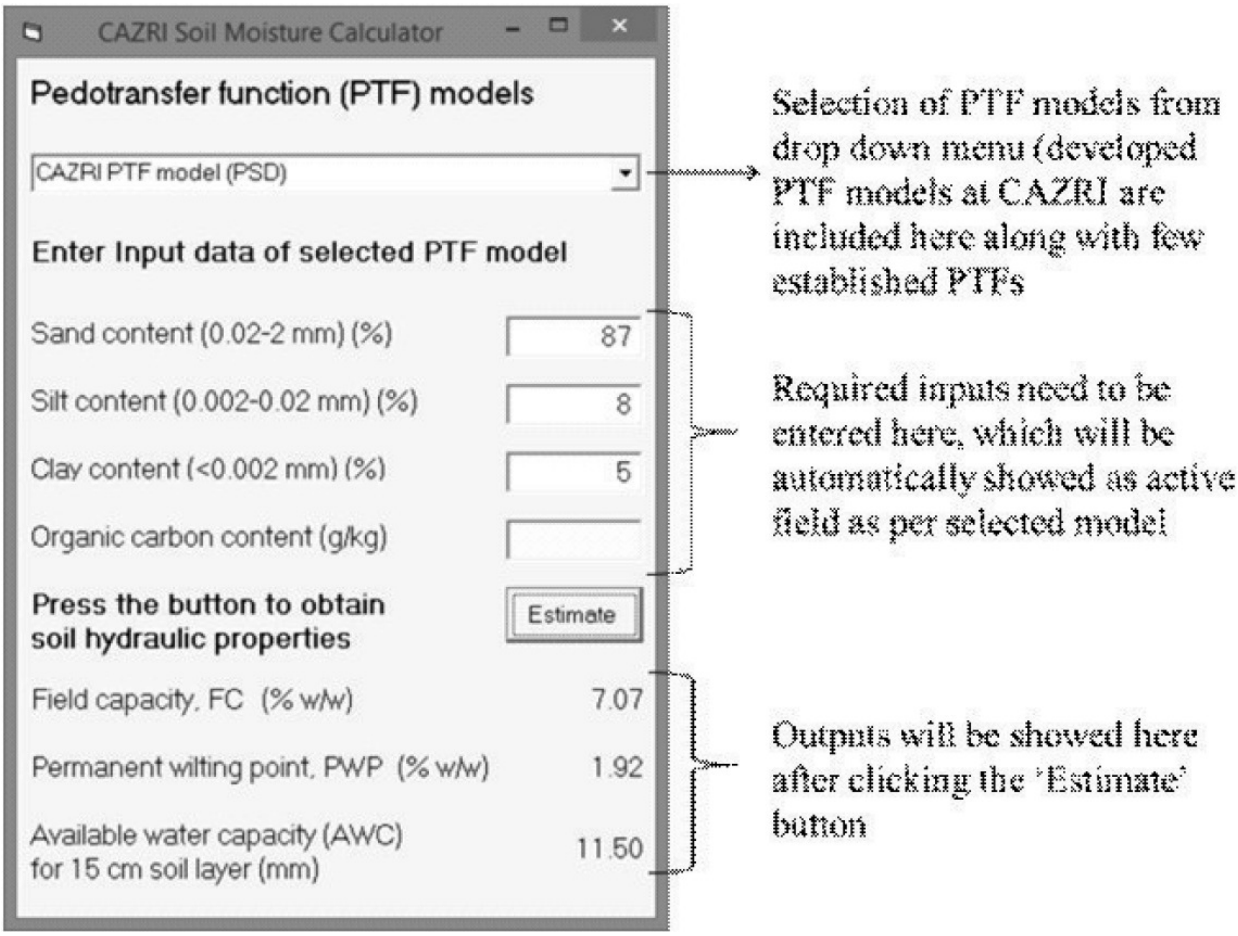

Fig. 10. CAZRI soil moisture calculator

3.5.2. *WebGIS application of digital soil maps*

WebGIS application for estimating soil water retention using PTF models is presented in Fig. 8. The central frame of the application helps to specify a location in arid western India for which soil wter retentionsare to be estimated. In the google map, the red baloon by default is located at the centre within arid western India boundary. By dragging the ballon within marked boundary of arid western India, the user can identify latitude and longitude ofthe location, which is diplayed at the top right frame. Otherwise, if the latitude and longitude of the desired location is known, it can be entered in the application to locate the field position withinin arid western India. The bottom right frame extract the information on basic soil properties from the digital soil maps, which is available in the background of the application. The extraction of information for a known geographical location from digital raster maps is done through postgreSQL query. Further, these basic information on soil properties are passed to middle left frame, which are to be used for PTF based estimation of soil water retention. At the top left frame, options are given to select a suitable PTF modelfor estimation of soil water retention. Finally after clicking, the 'estimate soil water retention' button, the user can get the value of water retention at FC and PWP, saturated hydraulic conductivity and van Genuchten water retention parameters. The application may be further extended to a decision support system, in which right decision can be made on irrigation water application.

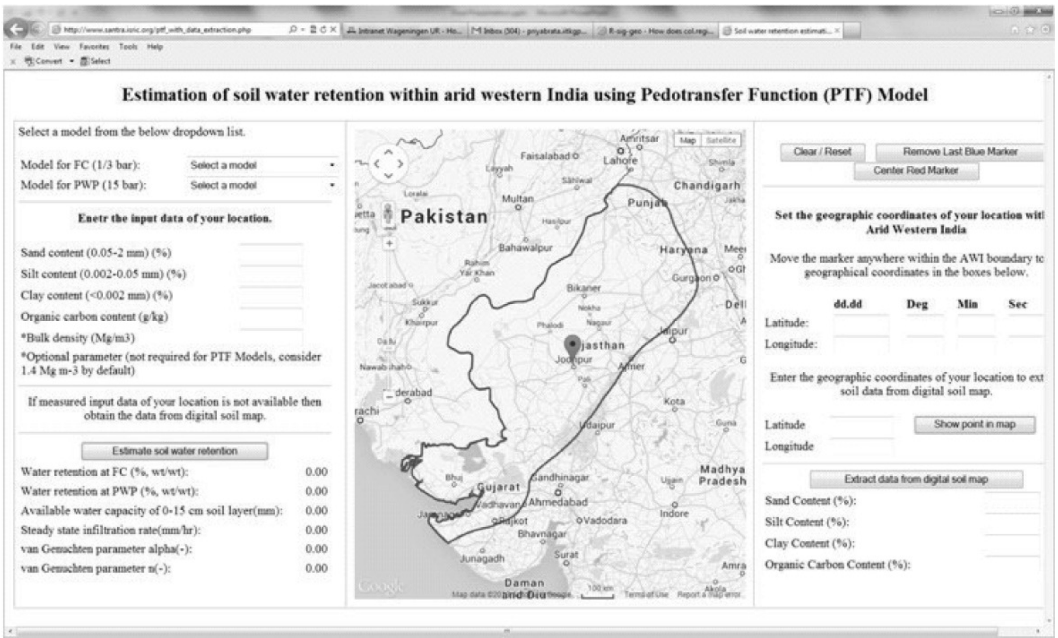

Fig. 8. Soil information system of arid western India in webGIS platform

3.5.3. *Mobile eneabled barcoding of soil archive*

Soil sample archives are traditionally stored in small containers with marked tags in a laboratory for any future use. Related soil database generated from these samples are generally available in hard copy either as bulletins or reports. Sometimes, these databases are also available in soft copy format e.g. excel spreadsheets. For accessing specific information on these soil samples or database, sometimes it becomes difficult to identify the samples/information from huge archive/database. For easy access to soil archives and database, mobile and web enabled barcoding system of soil archiveshave been developed at ICAR-CAZRI, Jodhpur (Fig. 9). Using the developed system, simply by scanning the barcode of each sample using an android app, an user can access information on soil sampling details and the determined soil properties. The application has the following two features: user access management and editing options to update soil database. Further, new soil data can be easily added in to the application. Users can use the application only after registering in the application with his login details.

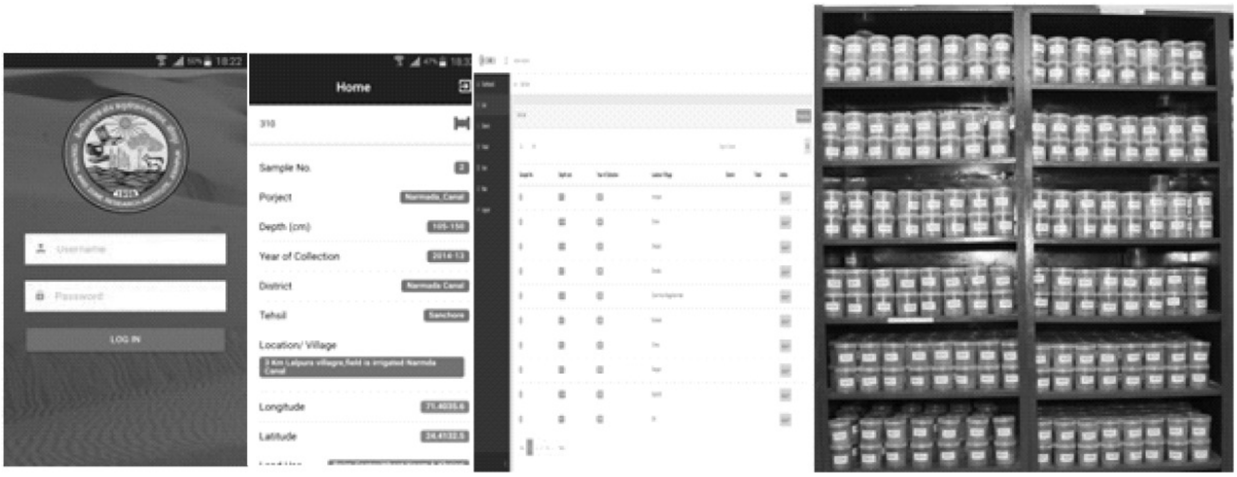

Fig. 9. Screen shot of mobile and web enabled barcoding system of soil archives

3.6. Handheld device on soil moisture calculator

A prototype of the handheld device to estimate soil water retention using PTF model has also been initially developed. Top view of the prototype is presented in Fig. 11. The dimesnion of the device is 14 ´ 8 ´ 5 cm. The device has four basic components: (i) PCB card, (ii) alphanumeric keypad , (iii) LCD display, and (iv) battery storage. The PCB card is coded with the PTF equations. Alphanumeric keypad is used to select the suitable PTF model and to enter the inputs on sand, silt, clay and SOC. Both inputs and outputs of the device are displayed in LCD of 3.5 ´ 2 cm. The device is operated by an in-built battery storage, which can be charged using an adapter. All these components are embedded in a casing prepared from aluminium sheet. Presently, the prototype is fabricated for providing a decision on irrigation water application. The prototype may be upgraded by including the options for nutrient management in which fertilizer application rate as per soil test reports may be calculated. Inout reading device e.g. camera, electronic sensors, communicating devices etc. may further be added to mae the prototype robust.

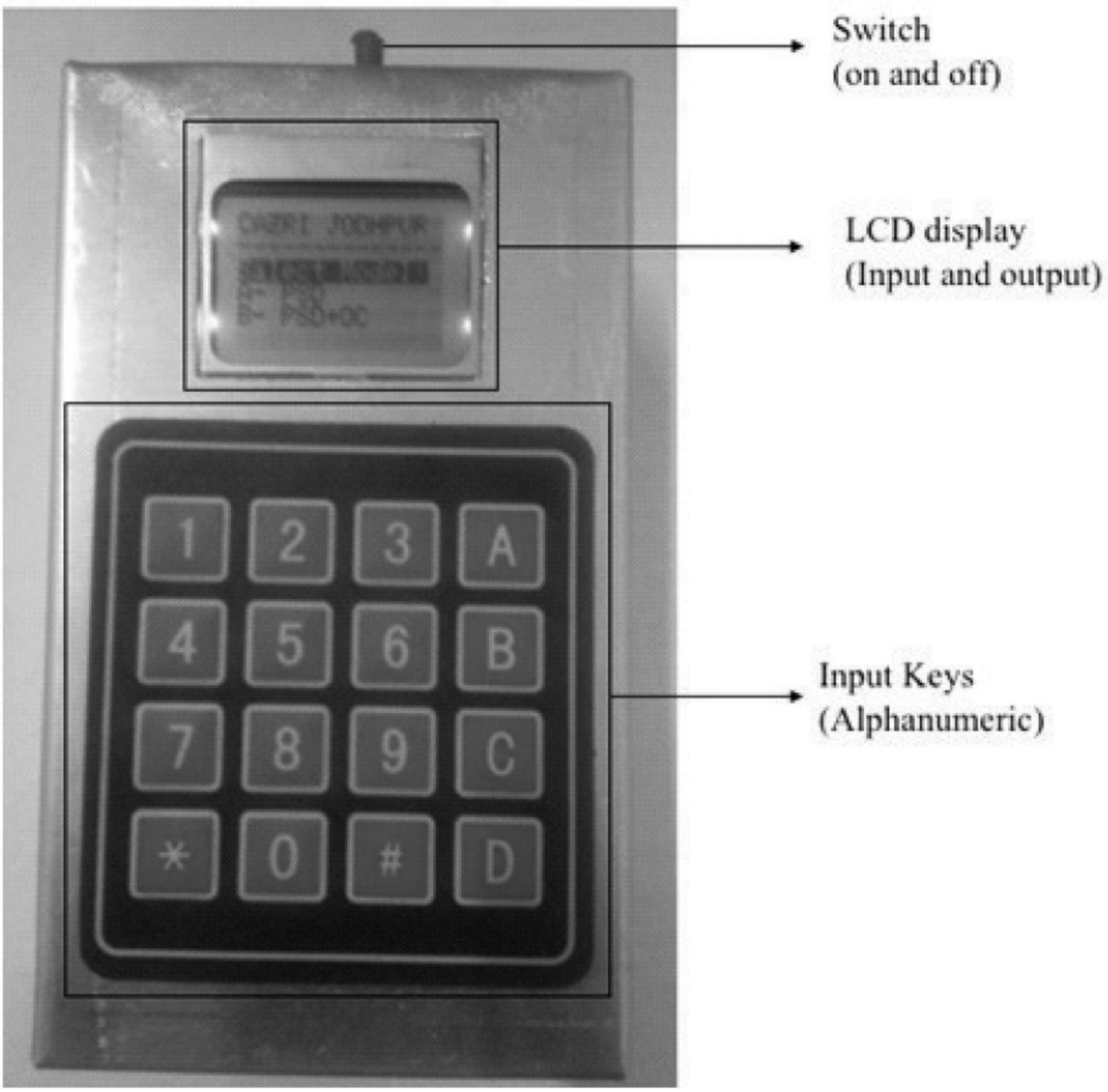

Fig. 11. Handheld device on soil moisture calculator

4. Conclusion

Artificial intelligence has been gained importance in recent times in different applications in our daily life e.g. speech recognition, smart home system, robot based medical surgery etc. With the advancement of 'internet of things' (IOT) technology in comouter science, it is now possible to communicate between devices and machines automatically. Moreover, a variety of machine learnng tools are now available to learn the complex linkages in databases, which enables us to develop predictive models with more accuracy than before. Furthermore, availability of information in digital platform make it easy for stakeholders to use and apply the required information for taking a quick decision. Therefore, application of these digital technologies in agricultural science is expected to make the farming community modern. Application of digital technologies in agriculture may also creates interests to educated youths of the country and thus attract them in agriculture. Since soil is a key resources in agriculture, its sustainable management is very important to support food production targets. In this paper, we discusses few potential options to apply artificial intelligence and digital technology in soil science e.g. digital soil library, soil property estimation through digital image analysis, digital soil maps, soil information systems in smartphones and computers, handheld devices for in-situ measurement of soil properties etc. These options are only few and there are so many to be done for future to make the agriculture systems more vigilant to detect rapidly changing environment and weather scenarios and to take suitabe decisions accordingly.

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