Chapter

A Methodology to Analyze Soil Moisture Characteristics Using GIS and Modeling Approach for Sustainable Crop Production

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Abstract

This chapter introduces the importance of soil moisture to attain optimum crop production. Various soil properties that play crucial role in managing irrigation system have been discussed. In addition, the lesson presents a detailed description of the in situ techniques for measuring the moisture content of different soils. In areas where field measurement of soil moisture is a cumbersome practice, remote sensing, GIS, and modeling have been emerged as a boon. The role of all three approaches has been studied to analyze the soil moisture characteristics of particular area to select suitable crop and cropping pattern. Salinity and waterlogging are two major problems caused due to improper and unbalanced transport of water and solutes in the soil. A complete methodology has been proposed which includes data collection and measurement of various soil parameters, estimating and simulating future salinity and waterlogging conditions based on current water management practices, quantifying severity levels of saline and water-logged areas and their effect on crop production and optimum policies for managing salinity and waterlogging for better crop productivity. The proposal is an integrated approach comprises of field as well as laboratory measurements, with efficient use of GIS, simulation, and optimization techniques.

Keywords: soil moisture, optimum crop production, salinity and waterlogging, modeling, GIS and optimization techniques

1. Introduction

Water is the principle resource that regulates the existence and growth of the earth's living beings. Agriculture is one prominent sector which consumes major quantity of available fresh water in the world, which is almost 80% of the world's water required for the society [1]. Studies state that around 70% of the water is used for irrigation purpose and out of that 15–35% of the water is not suitable for other purposes [2]. Various hydrological variables regulate and control the irrigation in agriculture. It is quite essential to plan and manage these variables effectively with special stress on climate change impacts causing failure in effect valuation and alleviation methods. Among hydrological variables, soil moisture is an acute physical element in several agricultural, meteorological, hydrological, and climatological processes. During rainfall, water stored in soil is the only source for plants growth and crop yield where available soil moisture influences decision on water management like sowing time, use of pesticides, fertilizers, herbicides, and irrigation scheduling [3–5].

Soil moisture efficiently predicts forthcoming crop yield and also significantly contributes to water safety in agriculture system [6]. It is a critical feature in agriculture system as it effects the movement of water, energy, and carbon between atmosphere and land surface. Soil water content is not only significant in sustaining crop growth but also is a chief connection in the water cycle of soil-plant-air range systems [7, 8]. As per [9], it considerably supports hydrological cycle in managing runoff, evapotranspiration, and crop production. Although, increase in use of this resource for meeting human requirement causes decrease in quality as well as quantity of groundwater resources [10], and the considerable quantity of excavation surpassed [11]. The constant decrease in groundwater table reduces soil moisture and its efficient water storage capacity.

Measurement of soil moisture is one of the main processes that can indicate the amount of water required for irrigation in case of its deficiency and type of crop that can be grown in case it is available more than requirement. Several numerical methods have been recommended and applied to determine soil moisture distribution and dynamics through different scales [12]. There are two methods for determining soil moisture: (1) direct and (2) indirect methods. In direct methods, gravimetric method is the most precise method while in case of indirect methods, frequency domain reflectrometry (FDR) and time domain reflectometry (TDR) give best results [13, 14]. Both the methods are quite accurate to obtain precise values of water content and are preferably performed by technicians by collecting soil samples for years to understand long-term moisture conditions of the soil of an area. Both these methods are time-consuming and cumbersome as well. Even though soil moisture value is significantly used in several processes like biochemical, hydrological modeling, and other related dynamic methods [15, 16], it is challenging and expensive to determine accurate dynamics of soil moisture due to high variation in spatiotemporal distribution of soil moisture on regional and global scale as well [17]. In such cases, remote sensing and GIS techniques offer distinctive chances of constant monitoring of soil moisture content values both spatially and temporally with high resolution at nominal expenses [18–20]. The datasets obtained from soil moisture analysis can be calibrated with remote sensing data for developing several physical and empirical models to predict soil moisture content spatially on large scale with high spatiotemporal resolution using GIS techniques [21–23]. Hence, in the last few decades, new approaches of remote sensing, GIS, and modeling have been developed which gives nearly accurate results with less efforts in minimum time.

Considering all the aspects, the paper has made a pivotal attempt to study and evaluate the soil properties influencing irrigation system, effect of soil moisture content on crop yield, various soil moisture content determination methods suitable for different areas, role of remote sensing and GIS in soil moisture analysis, and variation in quality and quantity of water content in soil which leads to several problems like salinity and waterlogging. Salinity and waterlogging are two main and common problems that decrease crop yield and gradually degrade the land quality. Hence, an introduction to the problems and their management approaches has been discussed. Further a methodology has been proposed which involves selection of a command area (Chambal command area) irrigated by canal system, soil conditions of the area, salinity and waterlogging problem occurring in the area, extension of problem with time, its impact on crop yield and land, analyzing the condition using an integrated approach (field measurement, GIS techniques, and modeling), and use of simulation and optimization both to get best solution to the problems.

2. Soil properties influencing irrigation management

Physical properties of soil determine the quantity of water (available in soil) that can be held for crop growth. When no more water is added to soil, life of plant is estimated by this detained amount. This water quantity governs irrigation recurrence rate and irrigation system type and capacity required to confirm constant growth of plant.

Soil system consists of three phases which include a solid phase (formed from organic matter, minerals, and several chemical compounds), a liquid phase (knows as the soil water content), and a gaseous phase (termed as the soil air). The soil particles are the key constituents in solid phase, and their various shape and size form the pore spaces of varying geometry. Both air and water fill these pore spaces in different proportions as per quantity of water available. A complicated multiphase system is developed due to the presence of solid particles, soil moisture, and soil air. A wide variation is found in volumetric configuration of the three main component of soil system. Other than above three components, in general, soil consists of several living organisms like bacteria (in majority), fungi, insects, algae, microorganisms, protozoa, and small animals which have direct or indirect effect on soil composition and crop growth. The soil properties that play imperative role in irrigating crops are infiltration rate and water-holding capacity, while other properties like structure, soil profile, texture, water table depth, and hydraulic conductivity also influence irrigation.

3. Soil moisture

Soil moisture content determines the amount of water present in the pore space. Variation in water content present in the soil is influenced by soil moisture, soil temperature, texture, microorganisms, and organic matter. Moisture in the soil can be sensed primarily from its temperature and surface soil moisture [24]. In general, soil moisture on the land surface is defined as water content on the upper layer of the soil, i.e. 5–15 cm. Even though water content in this layer forms very small part of the global water portion, it is quite significant and essential for physical, biological, hydrological, agricultural, chemical, and other global processes [25]. For this reason, precise data of surface soil moisture varying spatially and temporally are vital for managing water and land system and framing policies [26]. In that case, a proper irrigation management practice should be implemented on right time. The rise and fall in soil moisture content have direct impact on water intake and plant growth. Therefore, accurate measurement of soil moisture is quite important to know its availability for proper plant growth. Several approaches have been developed till date to analyze the soil sample for precise moisture analysis.

4. Measurement of soil moisture

Soil moisture can be measured on field using different methods. Among various field methods, dielectric soil moisture probes are used for unsaturated soil conditions which include frequency domain reflectometers (FDRs), time domain reflectometers (TDRs), and capacitance probes (CPs) [27]. All the aforementioned methods precisely measure soil moisture content and could be fully mechanized [28]. However, their installation and maintenance require intensive labor and attain accuracy at particular measurement point. Details of some popular methods for the measurement of soil moisture are given in the following sections:

4.1 Gravimetric method

This method measures soil water content of soil samples of specified volume or weight collected from field using a soil auger or sampling tube. At different sites for respective soil type, soil samples are collected from the required depth in air-tight aluminum containers. After weighing the samples, they are kept in an oven for around 24 hours at 105°C to drive off all the moisture. Once the samples are dried, they are removed from oven for gradual cooling at room temperature and weighed again. The change in weight of soil samples before and after drying gives the moisture content in the soil. Although the method gives accurate measurements, it is generally performed for experiment or research works.

Time consumed in oven-drying the samples is the only drawback of this method; hence, the development of various methods have simplified the soil moisture measurement process. In one such method, mixing of soil sample with methyl alcohol of specific volume is done and then difference in specific gravity of alcohol before and after mixing is measured using a hydrometer. In another method, calcium carbide is used in place of alcohol which reacts with water and forms acetylene gas. The change in weight of sample determines moisture in the soil. In recent time, rapid drying of samples is done by using infrared radiation.

Although, all the aforementioned or other recommended methods have not come in common practice.

4.2 Tensiometers

These are instruments which directly give measurement of soil persistency to hold water in it. The capillary or metric potential of soil is measured by them, and soil water content can also be estimated. The measurement procedure includes burying a water-filled pervious ceramic cup in the soil at any definite depth and connecting it with a vacuum gauge or manometer through a tube filled with water. In general, centimeters of water or hundredths of atmosphere-calibrated scales are used. Due to its high precision, a mercury manometer equipped with tensiometers is preferred in research works. While for field measurements, vacuum gauges are better options because of their simple design.

Tensiometer is quite unsuitable for measuring all the variety of moisture available in all type of soils. Perhaps they are best tools on fields to measure soil moisture conditions in wet range. These instruments are used most appropriately in sandy soils where huge amount of water available to plants detained at a tension of less than 1 atmosphere. In general, tensiometer is put at a desired depths showing soil root zone and field is irrigated when a set value of metric suction is reached in tensiometer. Hence, numerous tensiometers kept at different soil depths can be used to show quantity of water required for irrigation with the help of calibration curves. Hydraulic gradients in the soil profile can be estimated using these tools.

4.3 Pressure membrane and pressure plate technique

This technique was developed by Richards in 1949 and 1954 mostly used for doing laboratory analysis of soil moisture potential. The tool has strong air-tight metallic chambers (can resist pressure of 15 bars or more) enclosing ceramic pressure membranes or plates with valves allowing air entry of high pressure. The tool allows the formation of soil moisture characteristics curves of more than 1 bar metric potential which is not allowed on suction plates. The relationship between soil moisture content and soil metric potential is determined by firstly saturating the porous plates followed by placing the disturbed or undisturbed soil on these plates. Once the soil samples also get saturated, the plates are then kept in the metallic chambers. After exiting the diaphragm, the outlet tubes of plate are coupled with the chamber outlets. The chamber is sealed by closing it with desired force. To uphold required value of pressure, a compressor is used for regulating it to avoid any outflow from the chamber. When the pressure is applied, water present in the saturated samples of the soil begins to leak out from the outlet and continuously dribble until an equilibrium is attained against applied pressure. Thereafter, soil samples are oven-dried for weighted or volumetric measurement of moisture content. The soil water content can also be measured by comparing with other pressure values. For several soil samples, pressure values that can be selected are 0.1, 0.2, 0.33, 1, 3, 5, 7, 10, and 15 bars. The soil characteristics curve is developed using sets of moisture content and pressure data so determined.

4.4 Electrical resistance method

The dependence of electrical conductivity of a porous solid on the amount of water forms the basis of this method. Porous blocks containing electrodes inside, when embedded in soil, the water in the porous body come in equilibrium with soil moisture. The amount of water in the porous block (in equilibrium with moisture content) changes the electrical resistance between the two electrodes. The resistance is measured by a resistance meter. The blocks are calibrated against a range of moisture levels and are mounted in the field at the required depths. The electrode lead wires are taken out of the surface and well secured and protected against rain. When required, the resistance meter is carried to the field, and through the electrode the resistance is measured to know the moisture content from the calibration curve.

4.5 Neutron moisture meter

This is quite fast method to measure soil moisture on fields. It works on the principle that measures counts of hydrogen molecules in a unit volume of soil sample where it is being considered that equal number of water molecules are present in same volume of sample. The procedure includes insertion of a fast neutrons source and calculates the slow ones obtained.

The instrument contains two main parts (i) a probe, depressed in the vertically injected access tube in the soil. The access tube consists of a fast neutrons source and slow neutrons detector; (ii) a ratemeter or scaler (generally chargeable and movable) monitors the fluctuation of slow neutrons which is proportionate to the soil moisture content. The source of fast neutron could be a 2–5 millicurie mix of beryllium with radium or americium. In practice, the probe is depressed in the access tube and count rates are measured at the definite depth.

The method makes fast measurement of soil water content on field. The concept of neutron scattering method is to measure the quantity of hydrogen nuclei existing per unit soil volume which is directly related and corresponding to the quantity of water molecules present in same volume. The procedure includes injection of a fast neutron source and counting number of slow neutrons for water content measurement [29]. To attain appropriation counting, rates are adjusted and calibrated to totals obtained in a pure water tank and then standardized against volumetric measurement of soil water content.

5. Role of modeling and GIS in soil moisture analysis

Valuation of soil water content using satellite images [25, 30, 31] and surface air processing models [32] is therefore essential for obtaining spatiotemporal expansions like precise agriculture and real-time management. Though there is variable ambiguity and turbulence in climatic conditions, land irregularities and flora are yet to be explored for recognizing appropriate models for soil moisture assessment [28]. Visual data are preferred source for representing soil surface moisture from satellite sensors. The use of visual data over active microwave data is advantageous as former consists of huge high-resolution data storage and is upgraded to be collected functionally, for example, availability of Landsat images from 1972 [33]. Moisture content in the soil also has its influence on the spectral reflectance of the soil, though it affects changes through electromagnetic spectrum [34]. Soil moisture estimation from Vis-NIR (-visible-near infrared) spectrum through remote sensing has spectrally lesser effective domain due to baffling properties issues [35]. However, visible as well as infrared wavelengths have been successfully applied in estimating soil moisture using remote sensing data. Moisture in soil from 0 to 7.6 cm of depth can be estimated from the above wavelengths [34]. According to [26] (2020), perhaps soil moisture pattern estimation is preferred instead of specific water content. In their study, for estimating surface soil moisture, they have used a possible permutation of wavelength band instead of single band by executing four standard machine learning practices on five band dataset. In 2014, [27] has used 3.5 and 14 μm of thermal emissivity data soil moisture estimation. Studies on prospects of developing ratios and normalized difference (ND) processes for determining water content quantity in leaves have been performed [36–38]. A well-tested and verified range of normalized difference files and biophysical parameters like leaf area index, etc., have been suggested for soil moisture estimation [39–43], while several queries on application of variety of spectral bands wavelength for direct estimation of soil moisture are yet to be solved [42].

Most experts and researchers have successfully applied a wide range of algorithms using regression methods due to its simple methodology. Although, few arithmetic assumptions like inconsistency, outlier data, multiple symmetry and heteroscedasticity are needed to be considered which limits the use of conventional regression analysis method. To get over the above difficulties, several machine learning methods like random forest, decision trees, and neural network have been developed. Machine learning is a methodology which performs both automatic and semi-automatic assessment and analysis of wide range of datasets, aiming to develop significant relationships, configurations, and procedures among data [44]. In semi-arid areas, prediction of soil water content using remote sensing has been successfully performed nowadays by a common platform of machine learning techniques [43, 45]. Still, there are several distinct instances where machine learning is interestingly used in remote sensing for analyzing soil water content data. The advancement in machine learning approach resulted in improved efforts to evaluate soil water content from remotely sensed data [41, 43]. Soil moisture has an advantage that unconventional spatial data sources like land use and land cover maps which prevail at landscape scale can be used in the modeling [46]. Machine learning approach is specifically site-oriented; after calibrating the model, it can be applied only to related situations that are used for calibration [25]. Though, this approach can be applied to get important information regarding soil moisture assessment applied in areas that are not sampled or located at specific site [47, 48].

In countries with arid climate that are subjected to be profound to climate events, their economy considerably depends on agricultural sector. In arid climate, droughts are climatic events that occur periodically and are considered as big threat to both food safety and agricultural production of a country [49, 50]. In these regions where water stress is to be dealt by applying practices and advancement, best management options need the implementation of scenarios taking into account future soil moisture conditions and actual-time or near actual-time observations and allocations of soil moisture over prolonged areas. To achieve this, an easily accessible remotely sensed soil moisture data and a suitable model that can precisely interpret satellite data to soil moisture analysis should be implemented. Moisture in soil surface can be either be measured in the field using a suitable instrument [51] or analyzed by using remote sensing methods [5]. However, with the development and progression in land monitoring technology, the use of remote sensing for soil moisture estimation has also extended significantly since last decade [52]. Soil moisture on surface has been effectively retrieved using interpretations from both optical/thermal infrared and microwave sensors [28, 53, 54]. Particularly, microwave interpretations for the retrieval of surface soil moisture are quite radical, and various soil moisture products have been created [55, 56], namely the AMSR-E (Advanced Microwave Scanning Radiometer-EOS) [57], ASCAT (the advance scatterometer) [58], SMOS (Soil Moisture and Ocean Salinity) [59, 60], SMAP (Soil Moisture Active Passive) [61], and ESA CCI (European Space Agency's Climate Change Initiative soil moisture product) [62, 63]. The precision of these soil moisture products in the estimation of surface soil moisture has been enumerated by validating through either comparing various remotely sensed products or with field soil moisture measurements [64, 65]. Moreover, the remotely sensed products applications have been extensively increased in many fields like hydrology, agricultural, and climatic sciences [66–72]. However, there are still possibilities to expand the retrieval algorithm and exposure of questions scientifically on use and validation of these products. Furthermore, it is quite necessary to improve high spatiotemporal resolution soil moisture products [73]. High spatiotemporal resolution data for analysis of soil moisture can be obtained from various new satellite operations like Sentinel-1. At the same time, new methods and practices need to be introduced to develop the spatiotemporal resolutions of the prevailing soil moisture products, like the interaction between both optical/thermal and microwave soil moisture products.

Soil moisture is quite important factor for resisting drought, regulating flood [74, 75], and appropriate irrigation choices [76, 77] in crop yield. It is quite essential to obtain accurate estimation of regular patterns of soil moisture depletion for proper agricultural water resources management and improve crop production. Currently, the prediction models are formulated on the basis of conventional soil water content prediction methods primarily using empirical equations, linear regression, and neural networks. Most basic method used to design the model is empirical formula method. The initial soil moisture, daily precipitation, average temperature, and daily average saturation difference change and on the basis of multiple variant linear relationship of soil water content, [78] and others developed a method for a soil water content, rainfall, and drought assessment estimation model that can predict future drought for 5 to 10 days. The model gives policies for drought-resilient irrigation method; [79] used the empirical equation to predict the soil water content fluctuation along with TDR (time domain reflectometry instrument). The outcomes are similar, but the formula is quite easy and modest. Though the empirical formula is easy and convenient to use, the parameters have high spatial dependency and hence with change in area every time calculations are to be done again making the approach inefficient and time-consuming. With the rapid advancement in IT technology, several prediction models have been formulated [80] by collecting soil water content data from near-infrared reflection sensor, and the data are analyzed using multiple linear regression, subsequently showing 5.31% standard deviation in prediction. After analyzing meteorological data from gray correlation, the soil moisture trends can be obtained from predicted soil water content through a linear regression model designed by [81]. Linear regression models are quite unsuitable for nonlinear data and provide comparatively large errors due to inner limits and find it tough to meet prediction requirements. After the improvement in exercising the algorithm, both local and international researchers gradually started using neural network algorithms for soil water content prediction.

Soil moisture values had been predicted at various depths by giving different meteorological data as input in ANN, and the outcomes were found near to actual data [82]. Based on the above study, stimulation purpose of the neural network has been developed [83]. The conventional stimulation function was changed by an intricate number domain, and the grid was accomplished as per multiple-layer perceptron arrangement. The precise estimation had been improved by 9.1% as compared to conventional back-propagation neural network, obtaining the theoretical ground more precisely for soil water content estimation. A support vector machine had been used to elude a profanity of dimensional difficulties in neural network to predict soil moisture and improving accuracy to 89% [84]. On the basis of soil moisture features data, an improved algorithm for optimizing neural network has been obtained [85]. Due to random allocation of primary parameters in back-propagation neural network, the algorithm is trained with slow speed and certainly falls into regional targets. Hence, an optimal global primary data was found by introducing the genetic algorithm which speeds up the training effectively and increases prediction accuracy. Though soil moisture consists of complicated physical properties and meteorological parameters, it is quite difficult to develop a perfect mathematical model to predict soil water prediction. The physical properties and algorithm in conventional neural network are quite fragile to treat big data, having limited generalized scale and ability where further improvement in prediction accuracy is difficult.

In recent years, the scope and use of artificial intelligence are increased rapidly, in year 2006 [86] Deep learning (DL) has been recommended using multiple hidden layer structure to obtain well-classified and proficient big and varied characteristic data. Above neural network shows better computation control than conventional method and successful applications in search engines [87], image recognition [88, 89], prediction of stock price [90], and other fields. Few researchers have proposed deep learning for the analysis of soil texture and particle size to attain good prediction accuracy due to inconsistency and extreme complexity in soil pattern [91, 92]. On the basis of the above study, a soil moisture prediction model has been developed and optimized by using strong data processing efficiencies of deep learning to attain good prediction accuracy of soil moisture in Beijing [93].

6. Impacts of varying soil moisture content on crop yield

Conventional agriculture often uses excess water for irrigation which not only makes inefficient water utilization but also excess water generates problem of removal of essential nutrients and fertilizers in the root system which eventually reduces crop yield. Disturbances in soil profile occur due to both over and under irrigation. Both practices are harmful for crop production as under-irrigation lacks sufficient water while over-irrigation fills all the air pores with water causing no aeration which ultimately restricts plant growth. Variation in water content causes various problems such as drought, famine, acidity, alkalinity, sodicity, salinity, and waterlogging. Major problems that have been faced by most of the canal-irrigated areas are salinity and waterlogging. Salinity and waterlogging conditions reduce crop production, degrades land, and make crops out of cultivation if not treated on time. Therefore, focusing on these major issues related to soil moisture conditions, in the next sections an introduction to salinity and waterlogging with their management practices has been discussed. Furthermore, a completed plan to evaluate the problems and cope up with them has been presented.

7. Salinity and waterlogging

The rise in water intake in combination with climatic changes has caused critical water scarcity worldwide. Due to lack of water availability, several arid and semi-arid regions have started using poor-quality water for irrigating agricultural crops [94]. The use of poor-quality water and improper drainage disturb soil structure and make soil hard enough to allow water movement causing poor infiltration which further increases water table obtaining salinity and waterlogging problems and land degradation [95]. The chemical concentration and configuration of soluble salts in water decide irrigation quality. Usually, irrigation water quality is determined by considering fundamental standards like pH, electrical conductivity (EC), total soluble salts (TSS), total dissolved solids (TDS), residual sodium carbonates (RSC), sodium adsorption ratio (SAR), and ion toxicity [96]. Although, high TDS water is also suitable for irrigating crops with any risk to soil productivity only on the condition that proper irrigation management practices should selected to sustain prevailing salinity conditions in the root zone [97, 98]. Water with high TDS concentration raises sodium content, on drying make soil stiff, compressed, and impermeable to resist infiltration of irrigation water that facilitates soil salinity and waterlogging [99]. Waterlogging in arid and semi-arid regions occur due to the use of poor-quality water for irrigation water, faulty irrigation practices, and improper drainage facilities [97]. Presence of high TDS concentration and sodium content in soil water forms a shallow impervious layer (hardpan) which obtains waterlogging conditions and causes land degradation. Many studies have discussed the problems of salinity and waterlogging and their interrelationship [100–103]. These studies have determined that salinity and waterlogging adversely affect plant growth and crop production by decreasing air movement in soil and rising osmotic potential in soil solution. Further, sodium hazards cause potassium and calcium paucity in the soil, and waterlogging occurs due to damage to soil structure. Especially in arid and semi-arid regions, salinity has adverse effect on plant growth and crop yield leading to soil degradation [104]. Problem of salinity in soil arises either naturally due to weathered rocks and primary minerals or manually by the use of poor-quality irrigation water having high salt content [96].

8. Salinity and waterlogging management

For evaluation and monitoring of salinity and waterlogging conditions, remote sensing is one of the appropriate techniques. Identification of saline area can be done directly as well as indirectly by assessing spectral sign of white salt crusts on the naked soil surface or from indicators like halophytic plant and crop yield of salt-tolerant crops such as alfalfa, rice, and cotton, respectively [105–109]. To analyze salinity status in bare soil and vegetative behavior in saline area, some remote sensing indices like salinity index (SI), normalized difference vegetation index (NDVI), brightness index (BI), and normalized difference salinity index (NDSI) have been used [106, 110]. Several researchers studied a relationship between the on-field measurements of electrical conductivity and spectral indices imitated from satellite images [105, 111–113]. Various researches studied the correlation between salinity, waterlogging, and crop productivity. Waterlogged soil gets easily salinized as salts present in irrigation water are not leached out due to waterlogged conditions [114–116]. Refs. [97, 117, 118] reviewed the effects and management policies for crop yield in saline and waterlogged areas. In 2021 [119], the study predicted that changes in temperature and rainfall patterns related to climate change are main reasons for increased crop yield losses occurring due to saline and waterlogged conditions. Some management practices have been recommended to reduce soil waterlogged problem like improving drainage, growing waterlogged tolerant crops, and adapting nutrient management policies.

9. Methodology

A complete methodology on Chambal command area located in Kota district of Rajasthan, India, is described in the below section.

9.1 Problem formulation

In the Chambal command area, soils became waterlogged within a few years of the introduction of irrigation. Considering severity of soil salinity, the Government of Rajasthan in collaboration with Canadian Government implemented a drainage project during the year 1993 in Chambal command area to contradict salinity impact on agricultural production. In 2002, [120] had stated that in spite of the success of this project, some evidences of soil salinity hazards were seen during the first investigation survey of the Manasgaon command. Capillary rise is one of the reasons behind salinization of irrigated lands in the commands. Therefore, there is need to assess salinity and waterlogging in area with subsurface system installed and its subsequent effect on crop productivity.

9.2 Proposed plan of work

The plan is aimed at studying the impacts of irrigation on environment, i.e. salinity and waterlogging and subsequent effect on crop yield. It proposes an integrated approach which will include simulation model (SaltMod), Geographic Information System, and optimization procedures. All the data collected and measured will be processed for obtaining solutions for mitigating salinity and waterlogging problems in command area and improving crop yield. The flowchart of work plan is given in **Figures 1** and **2**.

9.3 Data collection

Data collection include (1) the study of published documents and materials such as air photo, satellite images, maps (e.g. topographic, geopedologic, and soils), (2) gathering of existing data related to climate, soil/groundwater salinity, and farming practices, (3) sampling design, and (4) field investigation and laboratory analysis [121].

9.4 Existing data

This part of the study entails collections and synthesis of available data from previous research projects. Available existing data will be utilized to identify and analyze the pattern of extension salinity and waterlogging with respect to land slope, geomorphology, and land use and land cover systems. The present data of electrical conductivity and land use and cover collected from selected points during former researches will be keenly observed for the study to find out general characteristics of soil. The topographic map will be collected from CADA, Kota, which will be used as base map for locating the observation points in the field. The contour map will be used for digital elevation modeling to understand the physical terrain of the study area.

9.5 Sampling design

The existing EC and geopedologic map will be used to get acquainted with the topographic features and salinity expansion in the research area. This data will be used

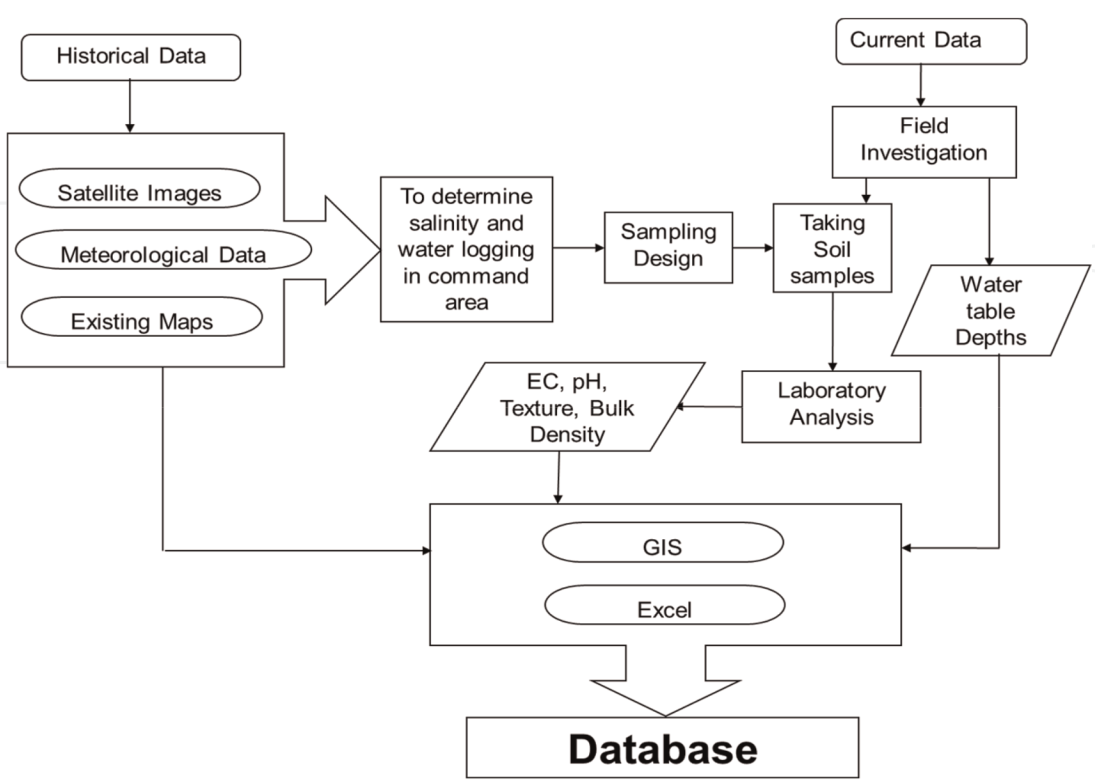

Figure 1.
Proposed data collection methodology.

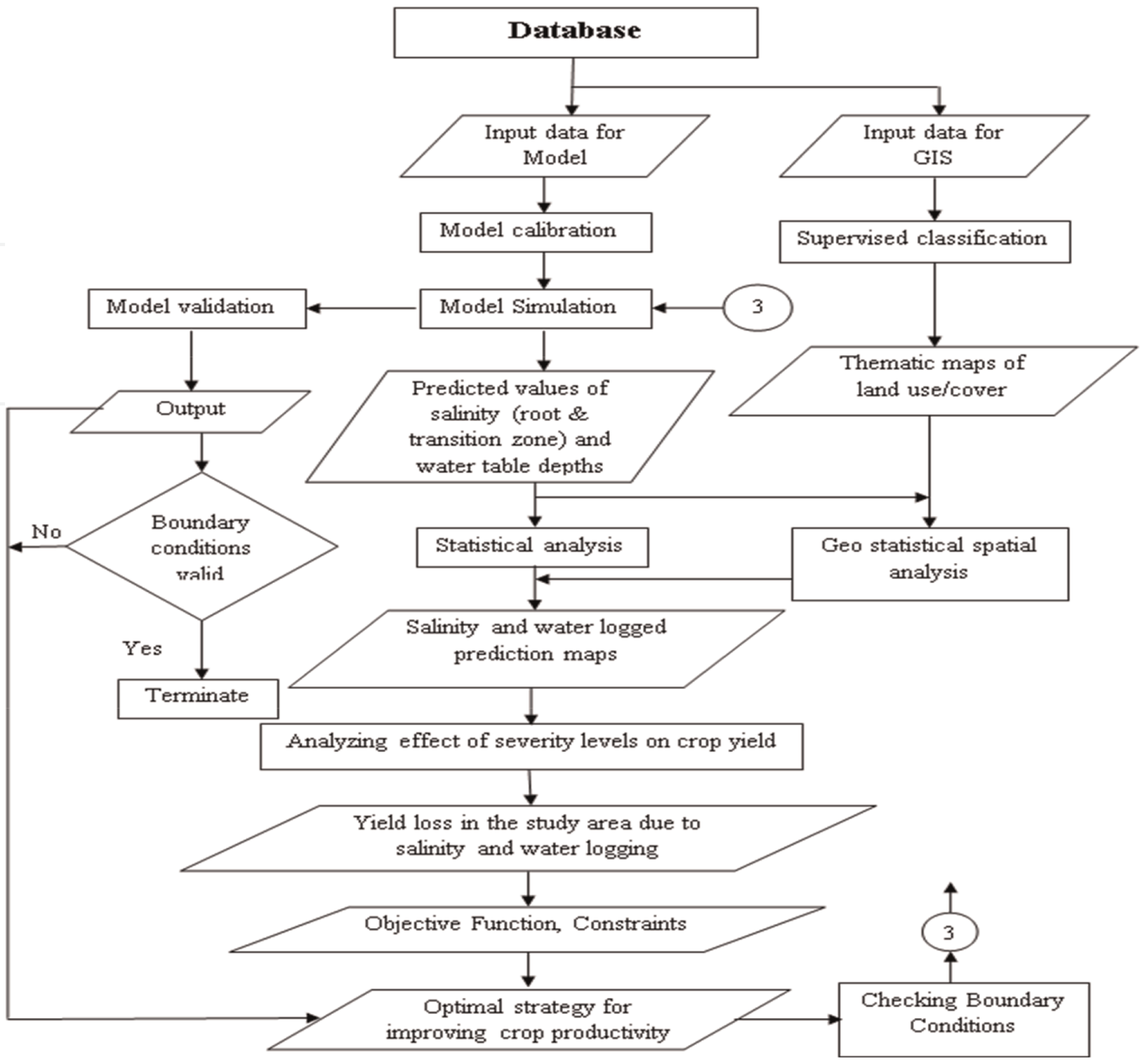

Figure 2.
Flowchart of proposed plan of work.

to choose an area for taking soil samples and/or splits to be assumed. An area of certain extent will be selected as sample area for field data collection and assessment on the basis of the idea behind selecting the same area from earlier researches and present geopedologic maps and current observation points taken into consideration. Sampling will be done through ArcGIS for generating observation points from which soil samples would be taken for analysis.

9.6 Field investigation

The main activities during fieldwork entails following steps:

a. *Soil sampling for EC and pH measurements:* Collection of certain number of soil samples from observation points generated in ArcGIS.

b. *Soil analysis:* Processing and analysis of soil samples collected from different locations for their physiochemical characteristics and classified according to the Soil Taxonomy.

9.7 Data entry and processing

Data entry and processing includes organizing and entering the collected data into Microsoft Excel worksheet. These data can be easily used in any tool for spatial (ArcGIS and G-stat) as well as statistical analysis tools (SPSS program). In addition to it, data in excel sheets can be saved or exported to other data formats (for example, CSV, dbf, and access) generally used by the majority of analysis tools. Hence, model outputs (EC, pH, and water table depth) and data from different sources (salt concentration and waterlogging pattern, salinity with respect to topography) will be spatially analyzed and interpolated using both the R software (Rcmdr and G-stat) and the GIS tool (ArcGIS 10.1) [121].

9.8 Selection of model

There are several approaches found in practice for modeling soil salinity and water table depths making diligent efforts attaining better understanding of expansion, dynamics, and relationship between them. Certain number of mathematical tools explain and compute elementary hydrologic processes and occurrence under a variety of conditions. The mathematical program combined with several computers and analysis skills are quite suitable for synthesizing theses correlated procedures and their interfaces to develop the optimum management technique for saline and waterlogged problems. Several software programs and models have been proposed for simulating salinity, groundwater depths, and solute transport which are analyzed in various research manuscripts. These models differ significantly in their design and function varying from easy to complicated, from crop-centered to soil-centered, and from broad to crop precise [121].

However, the availability of numerous models poses challenges on the selection of the selection and decides the best suitable model in certain situations. According to Ghassemi et al., selection of model and its success in simulation depends on numerous correlated aspects such as [121]:

1. The purpose of modeling exercise,
2. The complication of factors principally regulating the nature of the method,
3. The extent of acquaintance and information of system configuration,
4. The model factor assessment problem,
5. The quantity and quality of data existing, and
6. The modeling method occupied.

The proposal is recommended with main objective of predicting and identifying saline and waterlogged area in its initial phase of expansion. Though the rate and degree of salinity and waterlogging rely on several interrelating procedures, it is quite suitable to detect key procedure and explore basic explanation of these procedures. Therefore, this proposal is mainly based on applying simple modeling technique to predict long-term (decade) root zone salinity and prepare large-scale maps (field to region) of susceptible areas [121]. That means, although the predictions are not quite accurate, it may be significant once the prediction trend is clear.

Thus, in the present proposal, SaltMod is used as a tool for long-term prediction and expansion of salinity and waterlogging in the soil considering both spatial and temporal variation. Though, as the model is incompetent in spatial analysis and preparing maps, its gap will be filled using GIS technique to present by upgrading the physical and chemical processes to temporal and spatial scale of interest [121].

9.9 SaltMod model

SaltMod is a computer software program for predicting salt concentration in soil moisture, ground and drainage water, water table depth and discharge of drain water from irrigated lands for various hydro-geologic conditions considering varied water management options which includes groundwater use for irrigation and numerous schedules for crop rotation. The water management choices contain drainage, irrigation, and subsurface drainage water in wells, ditches, or pipe drains used for irrigation [122].

Computer models that are generally present for solute and water movement in the soil (e.g. Swap, Swatre, and Drainmod) work on the basis of Richard's differential equation for water transport in unsaturated soil combined with a differential salinity diffusion equation. The input data required for models include soil characteristics like relationship between soil water content, hydraulic conductivity, water tension, and diffusivity. There is of great variation among these relations from region to region, and it cannot be measured easily. These models run on short-term basis and need collection of enough daily databases of hydrologic processes occurring in the area. Thus, for any big project, the model can only be successfully applied using an expertise team with sufficient amenities [123].

This calls for a competitive computer modeling program which is simple and needs elementary data structure. Thus, SaltMod model was designed and developed by considering an ease of operation, simple data input to encourage its use among field specialists, engineers, project officials, and managers. The input data required for model are usually available or can be determined with justifiable accuracy or can be easily measured on fields. Though it is designed on the basis of numerical calculations that must be repeated several times, finally the output can be verified manually through the formula's mentioned in tool guide [123].

The main aim of SaltMod is to do long-term hydrosalinity predictions representing general trends not an accurate forecasting like the situation predicted would occur on the same date in next 10 years from now. Moreover, the model facilitates the option of drainage and well water reuse and also considers farmer's responses to salinity, waterlogging, water deficiency, and over-propelling from the aquifer. In addition to this, there is an option of introducing subsurface drainage system at different depths and discharges for obtaining an optimized system [123]. The current format is the model of a comprehensive version of preceding ones with a quite improved methodology. SaltMod model has been widely used and verified.

9.10 Calibration of model

Some parameters could not be measured, particularly leaching efficiency of the root zone and transition zone and natural drainage of the groundwater through the aquifer. Thus, prior to actually running the program for predictions, different values of above parameters are given as input and selecting those where soil salinities and groundwater depths output corresponds to actually measured values. Certain points from all observation points will be selected for calibration.

9.11 Model simulation

Prediction of future salinity and waterlogging will be done using present management practices. The predicted values of salinity in root and transition zone and water table depths in aquifer will be obtained as output. Further validation includes study of these outputs in detail and compared with measured values. SaltMod can simulate farmer's response to salinity and waterlogging. Besides, prediction with current condition model simulation for different scenarios is also proposed. Improper management practices, faulty farm practices followed by farmers, and inefficient subsurface drainage are main reasons causing both waterlogging and salinity. Therefore, the plan includes simulation for different management practices, farmer's preventive and curative measures, and subsurface drainage system in the selected area.

9.12 Validation of model

In order to evaluate model accuracy, comparison of simulated salt concentration (EC) values with the measured values for current year has been proposed. For validation, dataset will consist of points selected from observation points that will be used for the study. Validation will be performed for both depths (root and transition zone). Geostatistical approach using R-environment will be used to carry out the validation. The main purpose of using R-environment is the requirement of overlaying of various observation points spatially that are randomly collected from different places at different time. Hence, R-environment establishes prediction at the place of the validation points by providing spatial intersection abilities for several dataset points through geostatistical analysis [121].

9.13 Output data

SaltMod gives long-term predictions of each season in any year for number of forthcoming years on the basis of input data. The output table and graphs consist of salinity as well as hydrological aspects. These tables can be directly interpreted or evaluated through spreadsheet software. The examination completely depends on the conclusion ability of the user. The model provides quite worthy opportunity to obtain an assembly of relationship among various input data, outputs, and time. Several technicians may be desired to analyze impacts or interrelations between results. The model provides only an ample number of standard graphs, as it is unlikely to anticipate all several usages that may be prepared [123].

Output from GIS will include thematic maps showing status of salinity, water table depths, and crop yield. These maps will be used to understand relationship between them and mutual effect on each other. Further, the output from optimization will give optimal solutions for improving crop productivity in salt-affected and waterlogged areas.

9.14 Quantification of severity levels of salinity and waterlogging

After validating simulated and measured values, interpolated map will be exported from R-environment to ArcGIS (**Figure 3**). ArcGIS will quantify salinity and waterlogging based on severity levels as low, moderate, and severe.

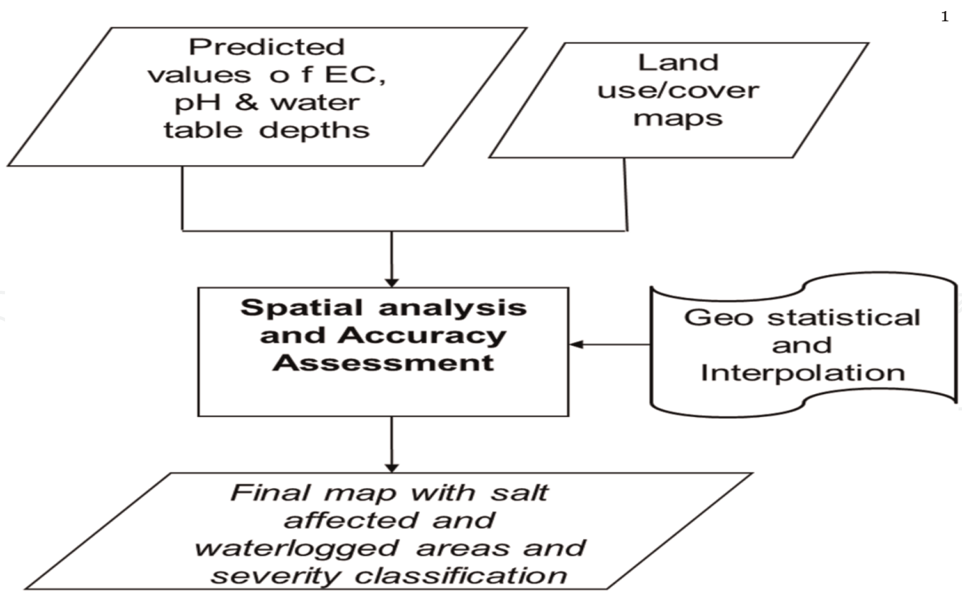

Figure 3.
Flowchart for severity classification of salinity and waterlogging.

9.15 Analyzing the effect of salinity and waterlogging on crop yield

As per **Figure 4**, effect of salinity and waterlogging at different severity levels on different crops grown in study area will be analyzed spatially through GIS. Further, their ultimate effect on crop yield will be estimated.

9.16 Generating optimal solutions for improving crop yield using model output data

Simulation outputs and crop yield output will be used for optimization as shown in **Figure 5**. For optimizing crop productivity, an economic optimization model has been

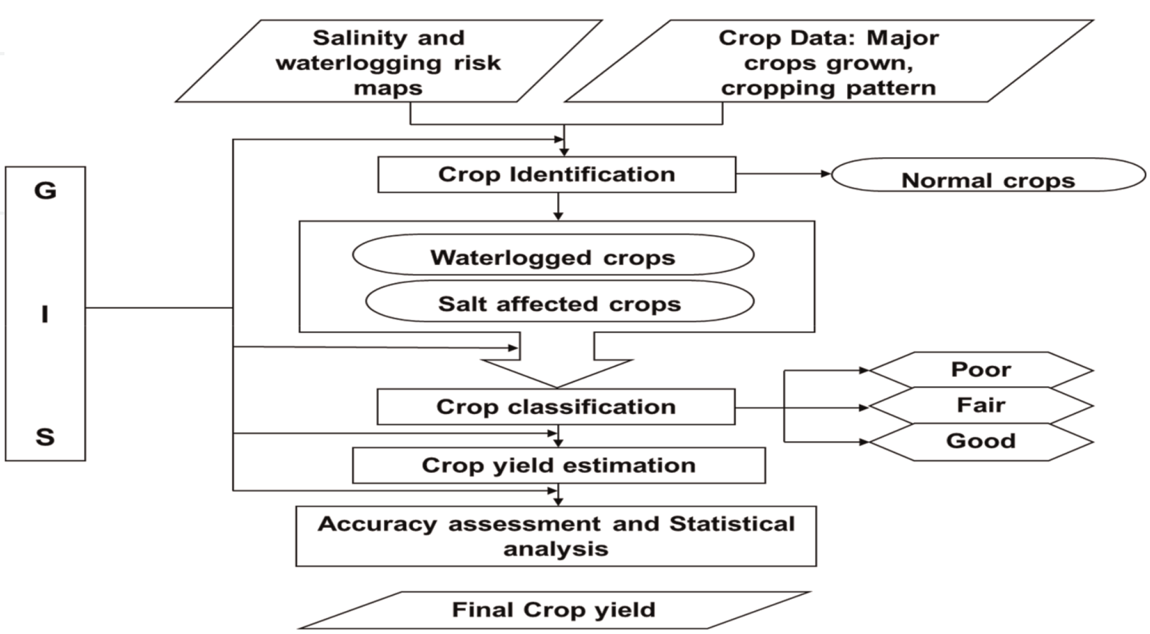

Figure 4.
Methodology for assessing effect of salinity and waterlogging on crop yield.

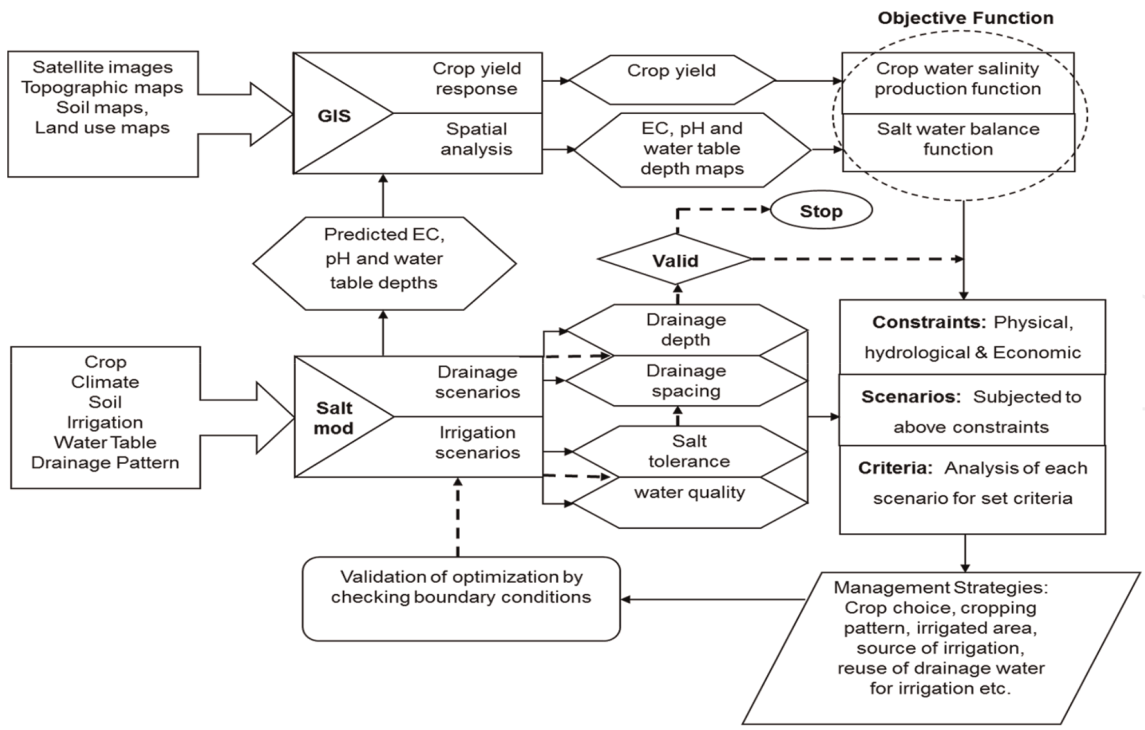

Figure 5.
Flowchart for proposed methodology of integrated approach.

proposed which includes hydrological-economic-environmental constraints and boundary conditions taken from the model generated data. When the solution is attained, the resultant outputs obtained from optimization will be put to the hydrosalinity model and run again for simulations. These values will be inspected for the verification of actual boundary conditions, particularly water table depths that have been dropped less than satisfactory limits. In case violation of boundary conditions has been disrupted, then groundwater uses are restricted and the optimization model is re-executed [124].

9.17 Significance of expected outcomes

The integrated approach will give effective management practices for dealing with problems in irrigated agriculture. Model capability for future prediction will be validated which can further be used for other projects with same conditions. Model will give relationship between various parameters responsible for salinity and waterlogging problems in command area. The proposed plan of work uses both in situ and computer technique for precise estimation of soil salinity and waterlogging conditions. Further, an integrated simulation and optimization approach helps in obtaining best solutions to above problems.

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