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Spatiotemporal Database Schema for Data Driven Applications in Smart Agriculture

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Abstract

Background: Data driven sustainable agriculture involves the collection, storage, processing, and analysis of enormous spatiotemporal data related to crop production processes, systems, infrastructure, and environment. Literature survey on smart agriculture research projects indicates that there is a need for improving handling of spatiotemporal data. There are gaps in handling spatial and temporal variability of parameters, division of crop field into management zones to reduce the variability for optimizing application of inputs such as fertilizers, water or pesticides. These gaps are to be addressed at design level of spatiotemporal database for smart agriculture. **Objective:** To engineer a spatiotemporal database schema that can be used for data driven sustainable agriculture. **Methods:** The methodology involves spatiotemporal data representation and modeling, Object oriented analysis and design of the database and Verification of the database using life cycle model and algorithmic steps. **Findings:** The resulting database is capable to store spatial and temporal variability of soil, plant and water parameters as well as handle spatial split, spatial merge, geometry and location changes of spatiotemporal objects. **Novelty:** Novel Use cases in smart agriculture along with spatiotemporal attributes are identified so that efficient applications can be realized. Adaption of the spatiotemporal database schema for Smart Irrigation System and its implementation methodology are presented.

Keywords: Spatiotemporal Database Design; Data-Driven Agriculture; Agriculture Informatics; Database Verification; Spatiotemporal Data Analysis

1 Introduction

Curiosity to process, analyze and understand the nature of data has been increasing tremendously in all sectors including agriculture. Many kinds of spatiotemporal applications require spatial and temporal data for modeling different entities. The availability of huge volume of spatiotemporal data related to smart farming in the future, often continually collected and updated, poses great challenges to our capability to understand the data and to extract potentially useful knowledge from it. But analysis of the data in spatiotemporal context and its use within the decision-making processes need research for representation and modeling spatiotemporal data, design and validation of spatiotemporal databases and applications.

The Motivation for this research is as follows. Agriculture is an important industry as well as the backbone of the economy for many countries. It plays an important contribution to Sustainable development Goals (SDGs) under the United Nations. The total population of the world, as revealed in November 2020 is 7.8 billion according to United Nations estimates. It is assessed that this number will be projectile to 8.5 billion by 2030 and 9.9 billion by 2050 [1,2]. With the rapid growth in the total population, food consumption is also growing rapidly worldwide. As the global population is growing higher, the food and agriculture organizations calculated that agriculture production will need to increase by 70% by 2050 to provide nutritious food to the whole population of the world. The emergence of new technological trends like artificial intelligence (AI), Machine learning, Big Data Analytics enable farmers to take a data-driven approach to collect and analyze large amounts of data to gain knowledge about the real-time status of their fields to improve farm yield and mitigate risks from weeds, pests, and diseases. The development of intelligent sensors, instrumentation and machines is beginning to play a crucial role in agricultural systems, which are affected by several factors such as environmental conditions, soil characteristics, water availability, harvesting practices, plant diseases, weeds, and other pests. In the near future, the integration of automated data collection and analysis, AI algorithms and decision support tools will provide advanced tools towards Precision Agriculture (PA). Moreover, robotic systems, on the ground and in the air, will also have a major role in bringing PA and digitalization to the field, for harvesting, pest control or data collection, just to name a few. The agriculture processes have been changing in order to enable technological adoption to move farm productivity, product quality, profitability and sustainable development to the next level. New Technologies like Internet of Things (IoT) sensors for measuring various parameters such as temperature, humidity, atmospheric pressure, illumination, electrical conductivity of soil are available to deploy in agriculture. Monitoring a farm using IoT sensors and use of data analytics can prevent low productivity of crops. One of the main challenges for the implementation of artificial intelligence in agriculture includes the low replicability and the corresponding difficulty in systematic data gathering, as no two fields are exactly alike. The information of interest in the agricultural sector consists of traits or features of systems that vary in space and time. Understanding how to manage agricultural processes implies considering many hundreds if not thousands of variables. Even within a single field, conditions are always changing from one zone to the next.

Food production and sustainable agriculture have been under increasing pressure due to global climate change and environmental deterioration [3]. This led to the use of smart sensors [4] in agriculture practices generating huge spatiotemporal data resulting in data-driven agriculture that employs Data Analytics (DA) to enhance effective decision-making capability, the operational efficiency and productivity in the agriculture sector [5]. Data-driven agriculture has potential to improve crop yield, reduce production cost, and ensure sustainable agriculture [2]. It involves the collection, storage, processing, and analysis of enormous, dynamic, complex spatial data related to all farming operations and processes [6]. The data can be sensor data, historical data, live streamed data, product business and market related data. Spatiotemporal Data Analytics and smart algorithms can be developed to predict the environmental changes and provide data driven solutions [5,7,8].

Spatiotemporal data help in building various potential Applications [9], such as Irrigation Management System, Pest and Disease Control, Controlled Use of Fertilizers, Farming Systems Monitoring, Livestock Monitoring, and Animal Health Monitoring. But research focus on spatiotemporal database design and its use for smart agriculture is not adequate. Two gaps identified in current smart agriculture research projects are 1. Inadequate provision to capture spatial and temporal variability of soil and plant parameters properly and 2. Lack of support to divide crop fields into management zones based on spatial and temporal variability. These problems are due to lack of provision in the databases to handle spatial split events, spatial merge events, and temporal changes to spatial and non-spatial attributes. The key contributions of this research article are to address the two gaps identified above at design level, offer provision to handle more Use cases in smart agriculture and discuss adaption of the database schema for smart irrigation system and its implementation strategy. The article describes representation of spatiotemporal data in section 2.1, modeling of spatiotemporal data in section 2.2, analysis, and design of spatiotemporal database schema in sections 2.3 and 2.4 respectively. Data driven smart agriculture platform is also discussed in section 2.5. Thorough analysis of how research gaps are eliminated in the design is provided in the results and discussion section. Adaptability of the database schema for smart irrigation systems is discussed in section 3.1.3.

2 Methodology

This section describes spatiotemporal data representation, reviews its modeling, object-oriented analysis and design of a spatiotemporal database and presentation of object relational spatiotemporal database. It then positions the database into a data driven smart agriculture context.

2.1 Spatiotemporal Data Representation

An object with at least one temporal and one spatial characteristic can be considered as spatiotemporal object. The spatial characteristics are geometry and location of the object. The temporal characteristics are time intervals or timestamps for which the existence of the object is true. The spatiotemporal object comprises temporal, spatial and non-spatial or thematic attributes. Moving Combine harvester, earthquake, forest fire and flood are examples of spatiotemporal objects. Changing values of thematic and spatial characteristics of a spatial object over a time are generally captured and represented as spatiotemporal datasets. The Spatial, Temporal and Spatiotemporal database objects and their mathematical representation are described in this subsection.

2.1.1 Spatial Data Representation

Spatial data identifies the location and shape of the objects on earth. Its management is very useful in applications in different domains such as natural resource management, global climate change and urban and rural planning and development. A geospatial object [10] can be defined using two components:

• Spatial component: It contains geometry (e.g., a point, line, polygon) of the spatial object and its topological relationship with other geographic objects (e.g., overlaps).

• Descriptive component: It contains a set of attributes

Mathematical notation for representing the Spatial component can be formulated as follows.

P = (x,y) Where P is a Point and x, y are real numbers.

PS = $\{ (p, q) / (p, q \,\varepsilon\, P) \wedge (p < q) \}$ where PS is a Set of Points, and $(p < q)$ means $(p.x < q.x) \vee ((p.x = q.x) \wedge (p.y < q.y))$

S= (b, e) where S is a Line Segment $\wedge$ (b, e ε PS) $\wedge$ (b $\neq$ e).

LS = $\{ (u,v) / (u,v \,\varepsilon\, PS) \wedge (u < v) \}$ where LS is a set of Line Segments

Polyline = $\{ (m, n) / (m, n \,\varepsilon\, LS) \wedge ((m.e = n.b) \vee (n.e = m.b)) \}$

Polygon = $\{ (l_1, l_2, l_3, ..., l_{k-1}, l_k) / (l_1, l_2, l_3,..., l_{k-1}, l_k \,\varepsilon\, LS) \wedge$

$(l_1.e=l_2.b) \wedge (l_2.e=l_3.b) \wedge ... \wedge (l_{k-1}.e=l_k.b) \wedge (l_k.e=l_1.b) \}$

In essence, a spatial object is characterized by its position or location, geometry and attributes.

Spatial Online Analytical Processing (SOLAP) [10–12] integrates spatial data into multidimensional databases. Spatial dimension [10] can be spatial, non-spatial or mixed. Spatial measures [10] can be analyzed along spatial and/or non-spatial dimensions. Spatial database research involves modeling, querying, analysis, and mining. This requires a spatial referencing system [13] to be incorporated into a spatial database.

2.1.2 Temporal Data Representation

A temporal data consists of built-in time aspects. It has its own geometry and topology. Instant and period are two primitives applicable to time dimension. Temporal point (TP) or instant is a location in a temporal reference system [13]. Temporal interval (TI) or a time interval, $[t_m, t_p]$ where t_m and t_p are time points and $t_m < t_p$, can be defined as a set of instants. It has a duration. Mathematical formulation for instant and time interval are given below.

TP = t where (TP = Temporal Point or Instant) $\wedge$ (t = Timestamp)

TI = $\{ [t_m, t_p] / (t_m = TP) \wedge (t_p = TP) \wedge (t_m < t_p) \}$

The time associated to an object may be valid time or transaction time. The valid time indicates that an object exists in real world during that time. The transaction time is the time when that element became part of the database. Bi-temporal databases maintain both transaction time and valid time for the objects. Valid time and transaction time can be a time point, time interval or period. A period is a combination of a set of time points and/or time intervals. Time is generally recorded for two basic facts – states and events.

2.1.3 Spatiotemporal Data Representation

Spatiotemporal database [8,14] concepts are the result of combining spatial and temporal data concepts. Therefore, a spatiotemporal database is a temporal record of spatial objects. This implies that changing spatial aspects such as geometry and/or location with time are captured simultaneously by spatiotemporal object. A spatiotemporal object can be represented as (NScT, ScT, T) where NScT is the time-stamped non-spatial conventional component, ScT is the time-stamped spatial component and T is the temporal component indicating its valid time. The spatial and non-spatial conventional components can take many values along the timeline. ScT is a set of records where each record contains a spatial component value at i^{th} time point, Ti. Similarly, NScT is a set of records where each record contains non-spatial component value at time point, Ti. All Ti's are contained in T and they do not intersect.

The mathematical model defining spatiotemporal data structure is given below.
SDS = (THC, SC, TC) where
SDS = Spatiotemporal Data Structure
THC = Thematic Component
SC = Spatial Component
TC = Temporal Component
THC = { (A,T) /A = Thematic Attribute Λ T = Temporal Attribute }
SC = { (S,T) /S = Spatial Attribute Λ T = Temporal Attribute }
TC = { T / T = Temporal Attribute }

Thematic Attributes are non-spatial properties of spatial objects whose values may change with time. Spatial Attributes are geometry and location of the spatial objects whose values also may change with time. Temporal Attributes are temporal point and temporal interval.

The practical classification of changes of spatiotemporal objects can be described as geometric change and thematic change. Geometric change can further be classified as born, growing, shrinking, dying and location change.

2.2 Spatiotemporal Data Models

A conceptual framework for describing and computing the real world is generally provided by a data model. The spatiotemporal data model is the key to handling spatial and temporal data because representation of spatio-temporal data and operations performed on such data are dealt by the model. The key issue is the representation and querying of spatiotemporal changes because it is primarily in this aspect that spatio-temporal databases differ from spatial databases. Spatiotemporal phenomena modeling and representation is also complex

Various models proposed [14,15] are Space-Time Cube, snapshot model, Space-Time Composite (STC) Model, Triad Model, Event-based Spatiotemporal Data Model, Spatio-Temporal Entity-Relationship (STER) Model, Three-Domain Model, The History Graph Model, Object-Oriented Data Models and Moving Object Spatiotemporal Data Model.

The snapshot model applies timestamp to layers and has the data redundancy problem. The Space-Time composite data model timestamps the attributes. The Spatiotemporal Object Model applies timestamps to spatial objects. An Event-based data model needs to merge changed states to the first layer to generate a recent state. Modeling using object-oriented data models is easy, but their implementation is difficult. Appropriateness of the spatiotemporal data model depends on the application that uses it. All these models provide weak support for spatiotemporal changes that involve more than one object such as split and merge. Most spatiotemporal data models [14,15] are reviewed, applied to land information system case study, and are critically evaluated and compared to identify open issues and problems for further investigation. The model used in this paper is object-relational model with provision to capture split and merge of spatial objects during their temporal evolution.

2.3 Spatiotemporal Data Analysis

Spatiotemporal data analysis [16] that integrates temporal and spatial aspects of the data leads to a more fundamental understanding of the dynamic processes involved in applications such as water management, Pest location and distribution analysis and traffic congestion analysis. A multidimensional model for exploratory spatiotemporal analysis focused on computational support for reasoning about data at various levels and at multiple dimensions. The concepts embodied in hierarchy theory are extremely relevant for analysis in the spatiotemporal domain. Hierarchical reasoning supports the study of scale and categorization effects in data analysis. Spatiotemporal analysis can be grouped as follows.

- Temporal data analysis
- Spatial data analysis
- Static spatiotemporal data analysis
- Dynamic spatiotemporal data analysis

Spatial dimension is fixed in temporal data analysis and then change in thematic attributes data with time is analyzed. Analysis of phenological parameters [17] of a crop over a time is an example of this category. Temporal dimension is fixed in spatial data analysis and then change of thematic attributes data with changing distance from a spatial reference is analyzed. An example of this category is analysis of change in humidity and temperature values with varying distance from seacoast at a given time. Thematic attribute dimensions and temporal dimensions are fixed in static spatiotemporal data analysis and then the spatial data are analyzed. Identifying regions having the same soil moisture at same time is an example of this type of analysis [18]. Thematic attributes dimensions are fixed in dynamic spatiotemporal data analysis and then changes in spatial attribute values with time are analyzed. The dynamic Spatiotemporal data analysis applications can be grouped into three major categories based on the kind of spatiotemporal data change.

• Applications dealing with location change of spatial objects with time: In this category of applications, objects change their location with time, but not their geometry or shape, for example, combine harvester moving in an agriculture farm for crop harvesting.

• Applications dealing with shape change of spatial objects with time. Two sub classes of this category are applications dealing with continuous change of shape of spatial objects such as forest fire and applications dealing with discrete change of shape of the spatial objects such as change of geometry of "land-parcels" or "rivers" in cadastral information systems. Spread of flood, spatial variability of soil and plant parameters [19] over time are examples that fall in this category.

• Applications dealing with both location and shape change of spatial objects with time. For example, a 'storm' or a cyclone is recorded as a moving phenomenon, which changes its location and geometry over time.

2.4 Spatio-temporal Database Design

Spatiotemporal Database Design involves study of different requirements of various spatiotemporal applications, the requirements analysis, and then design. Various types of spatiotemporal applications requirements are surveyed, an object-oriented analysis of the requirements and design of generic Spatiotemporal Database schema for applications is done and reported in [15].

There are two approaches to handle representation of various versions of a spatiotemporal object in the design.

i) Representation of changes at object level

ii) Representation of changes at attribute level

The first approach calls for creation of a new object identifier (oid) for each version of the object and chaining the object identifiers for tracking the object evolution. The second approach involves maintaining the same object identifier (oid) with versions linked to changing attributes. The attributes can be grouped into three categories.

i) Version Significant attributes

ii) Version insignificant attributes

iii) Invariant attributes

Updating the values of first category attributes is to be done in a non-destructive manner. The second category attribute values can be updated in a destructive manner. The third category attribute values are not allowed to be modified.

The mathematical representation of the relations in the spatiotemporal database designed in [15] is presented below. The L.H.S is the table name and R.H.S is the list of attributes in the table.

Spatial_Objects_Table = (Object_Id, Object_Geom, From_Time, To_Time, Object_Category, Object_Type, Change_Type, Gspi_Flag)

Split_Table = (Object_Id, New_Object_Id, Split_Time)

Merge_Table = (Object_Id, New_Object_Id, Mergr_Time)

Geom_Version_Table = (Object_Id, New_Object_Id, Change_Time)

Attribute_Info_Table = (Object_Id, Attribute_Id, Attribute_Name, Attribute_Type, Attribute_Category)

Version_Insignficant_Attribute_Table = (Object_Id, Attribute_Id, Attribute_Value)

Version_Signficant_Attribute_Table = (Object_Id, Attribute_Id, Attribute_Value, Version_From_Time, Version_To_Time)

Temporal_Table = (Change_Occur_Time)

Using this Spatiotemporal database, the applications for discovering History Topology and Topological Relationships of spatiotemporal objects are developed and reported in [15]. Systematic Survey on issues, tasks and applications of Spatiotemporal Data analysis and mining is described in [7,14].

2.5 Data-Driven Smart Agriculture Platform

Capturing data in agriculture using smart sensors [4] and developing potential spatiotemporal database applications [9] are crucial for digital agriculture. Information-based management cycle [20] for Data driven agriculture is described in Figure 1.

The platform refers to Soil, Plant, Water, Ambient and Sensors. It is the physical means for acquisition of data. Data includes the parameters measured from the ambient, crop and soil using the sensors [5,21]. The data goes through filtering routines [18], Statistical, Artificial Intelligence (AI) and Machine Learning (ML) techniques [5,19,22,23] for getting only the right data and correct decisions. Finally, Actuation refers to the physical execution of an action commanded by the decision system. As actions take place over the soil, crop, or ambient, the cycle starts. The responses of the soil, crop and ambient are then captured by specialized sensors and the loop continues systematically till harvesting time, which marks the end of the crop life cycle [20].

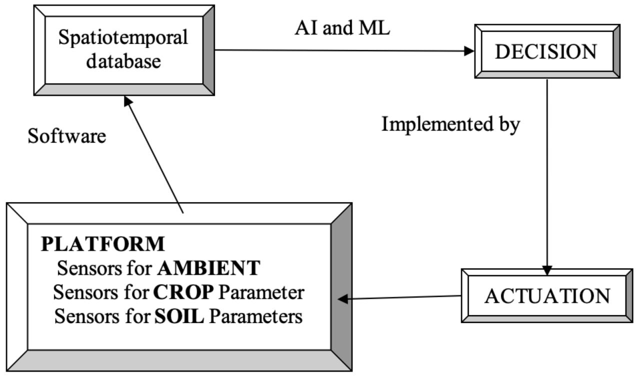

Fig 1. Information-based management cycle for Data driven agriculture

Regardless of how better the soil and crop are managed, a certain degree of spatial and temporal variability of parameters exists for all fields by nature. The variability is influenced by ambient and weather within a growing season and from year to year. Then, data for several years may be collected and analyzed to determine trends in parameters of interest. Hence data becomes a regular input into the farm information management system. Therefore, the necessity of monitoring soil and crops comes from the existence of variability, but it is required to manage this variability in a feasible way. A widely accepted method to do it is by dividing the field into subfields, called field management zones. As subfield areas will have homogeneous features, the crop management practices can be customized to each management zone. This results into a cost-effective and practical approach to Precision Agriculture. The adoption of management zones would reduce the usage of pesticides, reduce the cost of fertilizing, improve crop yields [22], and provide better farm records and information for decision management systems [20]. The taxonomy of various spatiotemporal database applications in agriculture is described in [4].

3 Results and Discussion

The database schema designed can store spatial and temporal variability of various parameters related to soil, crop, and weather. This is the key goal specified in future work in [19] to optimize application of fertilizers, water, or pesticides to the crops. The database can store the data with valid timestamps for multiple crop cycles for a few years. This enables construction of data warehouse solutions for crops. The database schema design is also supporting spatial split for each crop to create management zones (subfields) of the crop to maintain the variability within the limits. The data warehouse built in [12] can be enhanced by modifying its fact table to incorporate field management zones to have details at field zone level for better understanding of results and effective decision making. The database schema also incorporated spatial merge, location, and geometric changes of spatiotemporal objects to develop new applications for smart agriculture. As part of this, some of the Use cases in smart agriculture are identified and few Spatiotemporal Attributes for each Use case is described in Table 1 . The table also lists various references of the applications that can be reengineered using the spatiotemporal database schema of this paper.

Table 1. Spatiotemporal Database Use cases in smart agriculture

S.No	Use-Case	Spatiotemporal Attributes	Applications References
1	Smart Irrigation System	Subfields, Soil moisture and water-level of different subfields, nitrate concentration, Irrigation time schedule and volume of water, Soil temperature, Water level, salinity	(4,21,24)
2	Pest and Disease Control	Subfields, Crop Pest: Location, Disease Distribution, from date, To date, Pathogen identification, biology of pest, hosts, significance, detection and crop growth stage.	(2,4)
3	Crop Management	Subfields, Leaf area index (LAI), Phonological parameters such as the number of cropping cycles, length of season, and middle of season, soil moisture, soil temperature, water level, conductivity, salinity, Soil PH, Plant Nutrients levels	(3,9,17)

Continued on next page

Table 1 continued

4	Greenhouse Gases Monitoring	Temperature, Humidity, light intensity, concentrations carbon dioxide, methane, nitrous oxide, hydro chlorofluorocarbons (HCFCs), hydrofluorocarbons (HFCs) and ozone, Time period.	(5,9)
5	Tracking and Tracing agri-products	The origin, location, and life history of a product, the growing environment, production conditions, pest factors, management factors, storage conditions, transportation	(5)
6	Farm Management Information	Subfields, produce harvests and yields, scheduling farm tasks, profits-losses, tracking of soil nutrients, weather prediction, moving average, moving variance of soil parameters.	(2,18,20)
7	Automated Decision Making	Subfields, Soil parameters: Soil moisture, Soil temperature, Soil PH, Soil salinity, soil electrical conductivity, Soil Nutrients for plant growth, Environmental factors: Environment Temperature, Environment Light, Weather station data, air temperature, humidity, atmospheric pressure, illumination.	(1,6,18,19)
8	Monitoring Soil Nutrients for plant growth	Subfields, Non minerals (Hydrogen, Oxygen, and Carbon), Macronutrients primary: Nitrogen (N), Phosphorus (P), and Potassium (k), Macronutrients secondary: Calcium, Magnesium, and Sulfur, Micro-nutrients (Boron, Copper, Iron, Chloride, Manganese, Molybdenum, Zinc, Nickel), nitrate concentration.	(1,3,4,9,21)
9	Crop yield estimation	Subfields, vegetation indices, growth of infected areas and damage levels due to crop pest and disease, Leaf area index (LAI), Clay, silt, sand content (%), pH, phosphorous (P_2O_5), potassium (K_2O) and zinc (Zn) in Soil, precipitation, temperature, evapotranspiration	(2,4,22)
10	Data warehouse for agriculture	Subfields, Crop Parameters, Soil Parameters, Climatic conditions, Pest and disease parameters, Time period	(11,12)

Following discussion sections deals with the verification of the spatiotemporal database schema for providing justification on how it has achieved merits as mentioned in the results and its adaption to data driven smart agriculture.

3.1 Verification of Spatiotemporal Database Schema

The spatiotemporal database schema that is presented in previous section 2.4 is being verified to ensure that it could capture various changes of spatiotemporal objects during its lifetime. The verification is done using

i) Information Life Cycle Model
ii) Algorithmic steps for processes that change spatial objects
iii) Adaption of the database schema for a Use case in data driven smart agriculture

3.1.1 The Design Verification using Lifecycle Model

The values of spatial attributes such as geometry, location and non-spatial version significant attributes of the spatial objects may change with time. Whenever the value of the version significant attribute of any spatial object is changed, a new record is created with the values of the object identifier, attribute identifier, new value, and time of change. This new record is stored in Version_Significant_Attribute_Table of the spatiotemporal database. This provision in the design enables storage of spatial and temporal variability of soil, plant, and water parameters for optimization of application of fertilizers, pesticides, and water.

How changes of geometry and location of a spatial object were captured into the spatiotemporal database is described in the information life cycle model as shown in Figure 2 . The geometry of the spatial object, when first created, is stored in Spatial_Object_Table with its creation time. Whenever the object ceases to exist, its time is recorded in the same table. This facilitates capturing the parameters for entire duration of the crop cycle as each crop is stored in the table as a spatial object. Changes that occur to spatial object during its lifetime can be categorized as follows:

i) Spatial object splits into two or more objects
ii) Two or more spatial objects merge to form a new spatial object
iii) The geometry of the spatial object changes
iv) The location of the spatial object changes

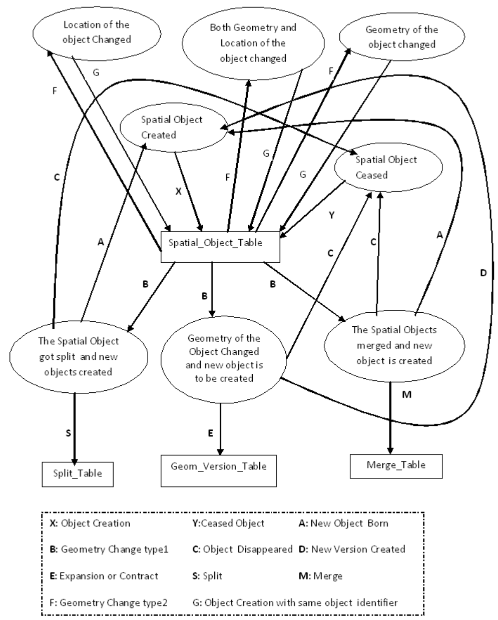

Fig 2. Information Life Cycle Model Showing Changes of Spatial Object with time

v) Both geometry and location of the spatial object change

Whenever any spatial object gets split into two or more objects, the details of split are recorded in Split_Table. The object that got split ceases to exist and the new objects, created due to split, are recorded in Spatial_Objects_Table. Handling spatial object split event facilitate division of crop into field management zones based on spatial and temporal variability of the parameters for customization of crop management practices. Whenever two or more spatial objects get merged to form new spatial object, the details of the merge are recorded in Merge_Table. The objects which participated in merge cease to exist and the new object created is stored in Spatial_Objects_Table. This feature of the database enables to merge field management zones to form larger one when spatial and temporal variability of the parameters for the zones is insignificant.

The geometry change that occurs to spatial object over time can be handled in two ways as discussed below. This helps in applications such as climate change and spatial spread of flood over time.

i) The time of change to the geometry of the spatial object is recorded in Geom_Version_Table and new geometry of the object is stored as a new spatial object in Spatial_Object_Table. The link between old object identifier and the new object identifier is maintained in Geom_Version_Table. The old object now ceases to exist.

ii) A new object with old object identifier is created to represent the geometry change and this new object is stored in Spatial_Object_Table. The creation time of old and new object is different even though their object identifiers are same.

The location change occurring to the spatial object is captured by forming a new version for the object with same identifier but with different time of creation and storing it in Spatial_Object_Table. The creation times of old and new versions of the object are different even though their object identifiers are same. This feature of the database facilitates tracking of farm equipment and products. If both location and the geometry of the object are changed, then this is captured by forming a new version for the object with same identifier but with different time of creation and storing it in Spatial_Object_Table. This feature of the database helps in cyclone tracking applications to represent spread and location of the cyclone.

3.1.2 The Design Verification through Algorithmic Steps

The algorithmic steps of formal process description for the changes of spatial object in the life cycle model are described below. Each formal step is numbered in sequence and brief explanation is give below the step if required.

Step 1. SO = (id, Geom)

SO is a Spatial Object type with its identifier (id) and Geometry (Geom).

Step 2. Create(s1: SO, t: Timestamp)

Store tuple (s1,t) into Spatial_Objects_Table as a new spatial object s1 is created at time t.

Step 3. Cease(s1:SO, t: Timestamp)

Update value of attribute To_Time in Spatial_Objects_Table with t for object s1 because spatial object s1 ceased to exist at time t.

Step 4. Split(s:SO, t: Timestamp) Return s_1,s_2, ..., s_k:SO
Cease(s:SO, t: Timestamp)
For i=1 to k, do
begin
Create(s_i:SO, t: Timestamp)
Store tuple (s.id, s_i.id, t) into Split_Table as a new record.
end
Step 5. Merge(s_1,s_2, ..., s_n:SO, t: Timestamp) Return s:SO
Create(s:SO, t: Timestamp)
For i=1 to n, do
begin
Cease(s_i:SO, t: Timestamp)
Store tuple (s_i.id, s.id, t) into Merge_Table as a new record.
end
Step 6. ChangeLocation(s: SO, t: Timestamp)
Cease(s:SO, t: Timestamp)
Create(s:SO, t: Timestamp)
Step 7. ChangeGeometry_Type1(s_o, s_n: SO, t:Timestamp)
Create(s_n:SO, t: Timestamp)
Store tuple (s_o.id, s_n.id, t) into Geom_Version_Table as a new record.
Step 8. ChangeGeometry_Type2(s_o, s_n: SO, t:Timestamp)
Cease(s_o:SO, t: Timestamp)
Create(s_n:SO, t: Timestamp)
Step 9. ChangeBothPositionAndGeometry(s_o, s_n:SO, t: TimeStamp)
Cease(s_o:SO, t: Timestamp)
Create(s_n:SO, t: Timestamp)

3.1.3 Usage of Spatiotemporal Database Schema for Smart Irrigation System

This section discusses how the spatiotemporal database schema, discussed so far, can be used in realizing "Smart Irrigation System" Use case. The smart irrigation system uses various sensors [4] and different methods for sensing [21] the parameters at regular intervals. The values of the parameters can be stored in the tables of the spatiotemporal database schema, as described in Table 2 .

Table 2. Spatiotemporal Databaseadaption for Smart Irrigation System

S.No	Parameter(s) Name	Spatiotemporal Database Table in which the parameter is maintained
1	Field	Spatial_Objects_Table
2	Subfields	Split_Table
3	Percent sand, Percent clay, Percent silt	Attribute_Info_Table, Version_Sinificant_Attribute_Table
4	Soil structure/peds size	Attribute_Info_Table, Version_Sinificant_Attribute_Table
5	Bulk Density, Particle Density, Porosity, Soil Permeability, Soil Temperature, salinity, water level, soil moisture, soil PH	Attribute_Info_Table, Version_Sinificant_Attribute_Table
6	Crop grown, Crop growth phase	Attribute_Info_Table, Version_Sinificant_Attribute_Table
7	Soil Nutrient Levels (Primary nutrients, Secondary Nutrients and macro nutrients), Nitrate Concentration	Attribute_Info_Table, Version_Sinificant_Attribute_Table
8	Air Temperature, Humidity, railfall, Environment Light, illumination	Attribute_Info_Table, Version_Sinificant_Attribute_Table
9	Volume of water released	Attribute_Info_Table, Version_Sinificant_Attribute_Table

Various attributes/fields identified for smart irrigation system and the corresponding tables of the database schema are mentioned in Table 2. The algorithmic steps specified in section 3.1.2 are used for creating these attributes and the database stores the spatiotemporal data for the agriculture farm as discussed in the Life cycle model. Once sufficient data is available in the database, an appropriate machine learning models need to be developed for dynamic irrigation scheduling so that the performance of application in[24] can be improved as the database schema has provision to create and maintain field management zones for optimal use of fertilizers, water or pesticides.

The implementation methodology of Smart Irrigation System deals with reading sensor values to database schema as discussed below.

i) Dividing the form field into zones based on various features such as slope, soil type, fertility values, crop to be grown etc.

ii) Installation of various sensors such as Moisture sensor, Humidity sensor, Temperature sensor etc. at identified location in the field for measuring values of the respective variables.

iii) Connecting the sensors to Arduino or Raspberry PI board. Connect both Arduino and Raspberry PI together to have plenty of sensors connected because

• Arduino Mega has 16 analog inputs, 4 UARTS, 54 digital inputs, 15 of those can be used for PWM. and all of them can be assigned as outputs by software, and a USB port.

• Raspberry Pi 3 has over 26 GPIO pins. But Raspberry Pi has only digital pins and no analog pins like Arduino. Raspberry PI can also be used for communicating the data to other systems.

iv) Following is a listing of few example sensors that can be connected to Raspberry PI.

• DHT11 and DHT22 humidity and temperature sensor
• BMP180 Barometer
• MCP3008 Soil sensor
• MQ Gas Sensor
• PIR Motion Sensor
• HC-SR04 ultrasonic sensor
• Magnetic Switch / Reed Relay
• GP2Y0A02YK infrared distance meter
• RFID-RC522 – Inductive RFID card reader
• MPU-6050 Gyroscope

v) A multithreaded python program is to be loaded into Raspberry PI to configure and carryout following tasks.

• Read the sensors data and do required calibration. It uses spidev and time packages of python.

• Install Raspberry-gpio-python or RPi. GPIO Python module to control the GPIO interface on the Raspberry Pi and gpsd-clients Module to communicate with the GPS daemon that in turn communicates with the GPS receiver for getting latitude and longitude information. GSM/GPRS module can be used to establish communication between a computer and a GSM-GPRS system.

• Pack the sensor data and send it to the connected clients. It uses python socket programming. The server software runs in Raspberry PI and Client runs on field server.

vi) Install PostgreSQL, Post GIS and create the database schema using SQL. Connect to Raspberry PI using the Python socket client module, then receive the data from Raspberry PI and store it in the database.

vii) As the field server is limited in its storage and processing capacity, the data from the field server can be loaded into Spatiotemporal Big Data Processing System such as ST-Hadoop or Beast or JUST. Apache Flume tool can be used for this purpose.

viii) The spatiotemporal big data can be used to build and test machine learning and deep learning models for using in decision making in Smart agriculture. The Apache Mahout or Spark MLLib can be used to build machine learning models.

4 Conclusion

The fundamental nature of Spatial, Temporal and Spatiotemporal data and its modeling is analyzed and described well. The literature survey addressed requirements of spatiotemporal applications and object-oriented analysis and design of spatiotemporal database. The generic spatiotemporal database schema to support spatiotemporal applications in smart agriculture is presented. The database schema is verified using the Life Cycle model. A detailed discussion is provided on how the database schema is managing spatial and temporal variability, handling spatial spilt for creating crop management zones, managing spatial merge, geometry and location change of spatiotemporal objects. The algorithmic steps for verification of the database changes for various processes are elaborated. The literature review also addressed the use of the spatiotemporal database schema in the development of prototype applications using open-source software Postgresql along with PostGis and Java for discovering evolution of spatiotemporal objects and topological relationships among spatiotemporal objects. An integrated platform for advanced agriculture that enables usage of spatiotemporal data analysis for decision making in smart agriculture is discussed. Various Use cases in smart agriculture that can make use of the spatiotemporal database schema are identified and presented. Adaption of the schema for Smart Irrigation System indicates that the proposed spatiotemporal database schema acts as a base to realize the Use cases and develop applications for various spatiotemporal data analysis and mining tasks in data driven smart agriculture. The future research involves development of machine learning models for smart agriculture in collaboration with Agriculture Scientists for automation of farm sector.

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