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Mexican Soil Mesh (MSMx): A Web Service for Efficient Management of Soil Data in the Continental Shelf of Mexico

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Abstract: The Mexican Soil Mesh (MSMx) web service emerges as a pivotal tool for researchers, farmers, and policymakers in the efficient management of extensive soil databases. Built on a responsive and intelligent web design, MSMx synchronizes seamlessly with the SQL language, allowing users to selectively download variables tailored to their studies at the desired spatial scale. The programmatic structure enhances query speed, optimizes development times, and incorporates satellite programming modules for effective handling of the vast soil dataset. This paper highlights the key features, benefits, and applications of MSMx, emphasizing its role in facilitating data-driven decision-making processes and promoting sustainable soil management practices on the continental shelf of Mexico.

Dataset: https://clima.inifap.gob.mx/lnmysr/DatosIndirectos/MSMx Certificate of intelectual property is in progress

Dataset License: license under which the dataset is made available (CC0)

Keywords: soil parameters; web service; MSMx

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1. Summary

With the rapid advancement of satellite design, digital technology, and cloud computing, an increasing amount of data is generated through digital equipment and sensors, such as satellite constellations, smartphones, computers, and advanced measuring infrastructures [1]. For example, the size of data on the internet is now measured in exabytes (10^18), zettabytes (10^21) [2] and Yottabyte (10^24). However, the collected ground data and the estimated data are experiencing exponential growth, and their structure is also becoming much more complicated. The processing and analysis of these large-volume data pose both a new challenge and an opportunity with the concept of "big data" [3,4]. Indeed, in recent years, big data has gained increasing importance in tech services, data engineering, production systems, and environmental monitoring, leading to significant changes in data management in developing analysis techniques.

Database Management Systems (DBMS) have evolved to handle the growing demand for data storage, processing, and analysis. Traditional data is structured data managed by computing programming experts within organizations. In a traditional database system, a centralized architecture is used to store and maintain data in a fixed format or fields in a file. For managing and accessing the data, Structured Query Language (SQL) is utilized. Its high level of organization and structure makes it easier to store, manage, and analyze. Traditional data is crucial for decision-makers. Big data can be considered as an advanced version of traditional data, dealing with excessively large or complex datasets that are challenging to manage using traditional data-processing application software. It involves a large volume of structured, semi-structured, and unstructured data.

Big datasets are increasingly relevant in the decision-making process. Concepts like precision farming, digital agriculture, and machine learning drive innovation in production chains. Traditional production systems are grappling with issues such as water shortages, drought, and soil exhaustion. Smart grids offer effective solutions to accelerate sustainability in production systems, enhancing the preservation of natural resources. Despite the growing awareness of sustainable development to address climate change effects, it presents significant challenges to smart farming and the stable operation of food production chains. In this context, soil data are critical.

In a collaborative effort coordinated by the Food and Agriculture Organization of the United Nations (FAO), the best available (newer) soil information for central and southern Africa, China, Europe, northern Eurasia, and Latin America was combined into a new product known as the Harmonized World Soil Database (HWSD) [5]. Until recently, the HWSD was the primary digital map annex database available for global analyses. However, it has several limitations [6–9]. Some of these limitations relate to partly outdated soil geographic data and the use of a two-layer model (0–30 and 30–100 cm) for deriving soil properties. Others concern the derived attribute data themselves, particularly their unquantified uncertainty, and the use of three different versions of the FAO legend (i.e., FAO74, FAO85, and FAO90). These issues have been addressed to varying degrees in various new global soil datasets [10–12] that still largely draw on a traditional soil mapping approach [13].

In the last decade, digital soil mapping (DSM) has become a widely used approach to obtain maps of soil information [14]. DSM involves primarily building a quantitative numerical model between soil observations and environmental information acting as proxies for the soil-forming factors [13,14]. DSM can also integrate direct information as proxies for soil properties, such as proximal sensing measurements. The number of studies using DSM to produce maps of soil properties is continually growing. Numerous modeling approaches are considered, from linear models to geostatistics, machine learning, and artificial intelligence (e.g., deep learning). [16] provide a recent review of methods and applications in the field of DSM.

The significant progress in information and communication technology (ICT) provides a new vision for farmers, academics, researchers, and policymakers to perceive and promote the transformation of traditional production systems into smart production systems. Embedded critical data associated with crops' water demand and biotic and abiotic stress requires near real-time data, including field measurements and control instructions, transmission, storage, and analysis in a fast and comprehensive way. This paper aims to discuss the concepts of grid soil data framing and its applications. The intent of this paper is threefold. First, the gridded soil data are embedded in one specific data frame. Next, the paper briefly reviews the concepts of web services, friendly user navigation, and hierarchical query. Finally, the manuscript illustrates the detailed applications of soil data analytics in smart grids and point centroids in the Mexico domain. The objective of this study was to create a continuous dataset of soil properties specific to Mexico's domain, referred to as MSMx (Mesh Soils Mexico). This database includes regional predictions of physical, chemical, and derived soil properties. These properties encompass soil organic carbon content, total nitrogen, coarse fragments, pH (water), cation exchange capacity, bulk density, and texture fractions at six standard depths (up to 200 cm; see Table 1). Soil physical properties pertain to the structural organization of soil and are indicative of its architecture [17]. Chemical properties depend on the soil's chemical composition. Derived properties, such as porosity, air capacity, water capacity, compaction, effective root depth, carbon sequestration, and carbon sequestration potential, necessitate the application of response models to interrelate physical and chemical properties. Table 1 provides a complete list of soil properties included in the MSMx geodatabase.

2. Data Description

2.1. Data origin

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[17] presented a comprehensive overview of the global soil dataset SoilGrids, a mapping tool that generates global soil property maps at medium spatial resolution (250 m cell size) using advanced machine learning techniques. The dataset utilizes soil observations from approximately 240,000 locations worldwide and incorporates over 400 global environmental covariates, encompassing factors such as vegetation, terrain morphology, climate, geology, and hydrology. The native format of SoilGrids consists of two-grade global patches in GeoTiff format.

Table 1. Soil properties and units contained in the MSMx geodatabase. The distribution of soil particles, including sand, silt, or clay, is known as soil particle size distribution.

PROPERTY	ACRONYM	DESCRIPTION	MAP UNITS	CONVERSION FACTOR
PHYSICAL	BDOD	Bulk density of fine soil fraction	cg/cm^3	100; to get kg/dm^3
	CLAY	Proportion of clay particles (< 0.002 mm) in the fine soil fraction.	g/kg	10; to get g/100g (%)
	SAND	Proportion of sand particles (> 0.05 mm) in the fine soil fraction.	g/kg	10; to get g/100g (%)
	SILT	Proportion of silt particles (≥ 0.002 mm and ≤ 0.05 mm) in the fine soil fraction.	g/kg	10; to get g/100g (%)
	CFVO	Volumetric fraction of coarse fragments (> 2 mm)	cm^3/dm^3 (vol‰)	10; to get $cm^3/100cm^3$ (vol%)
CHEMICAL	CEC	Soil Cation Exchange Capacity	mmol (c)/kg	10; to get cmol(c)/kg
	NITROGEN	Nitrogen (N)	cg/kg	100; to get g/kg
	SOC	Soil organic carbon content in fine soil fraction	dg/kg	10; to get g/kg^{-1}
	pH	Soil pH	Ph x 10	10; to get pH
DERIVED	OCD	Organic carbon density	hg/m^3	10; to get kg/m^3
	OCS	Organic carbon stocks	t/ha	10; to get kg/m^2

2.2. Soil parameters description

- Bulk density (kg/ m-3). The organization of individual soil particles into larger units makes the soil a porous medium, which makes it possible to establish two types of densities, the density of the particles (mineral and organic) or real density and that of the soil as a whole or bulk or apparent density [19].
- Proportion of clay particles (weight %). It is the smallest particle (less than 0.002 mm) in diameter.
- Proportion of sand particles (weight %). The largest soil particle (2.0 mm - 0.05 mm).
- Proportion of silt particles (weight %). The silt has an intermediate size (0.05 mm - 0.002 mm).
- Volume fraction of coarse fragments (vol %). Particles larger than 2 mm in size are referred to as rocks, stones or gravel and are not considered soil material.
- Cation exchange capacity (cmol+/kg). According to [6], it is a measure of the amount of negative charges present on the surfaces of minerals and organic soil components (clay, organic matter or humic substances) and represents the amount of cations that the surfaces can retain (Ca, Mg, Na, K, NH4 etc.). These will be exchanged for other cations or hydrogen ions present in the soil solution and released by the roots. A soil with low CEC indicates low ability to retain nutrients, sandy or poor in organic matter.
- Nitrogen content. Soil nitrogen is one of the most important elements for plant nutrition and most widely distributed in nature. It is assimilated by plants in the cationic form of ammonium NH4+ or anionic form of nitrate NO3-. Despite its wide distribution in nature it is found in inorganic form so it cannot be assimilated directly.

- Soil organic carbon (SOC; ‰ (g/kg-1)). The global organic carbon pool is approximately 1,550 gigantons of carbon, which is twice as much as the atmospheric carbon stock and 150 times the current emission of fossil fuel emissions [20]. SOC significantly affects soil fertility and crop yield, and plays an important role in adjusting the global climate [21]. Soil organic carbon is a measurable component of soil organic matter. Organic matter represents 2% to 10% of the mass of most soils and plays an important role in the physical, chemical and biological function of agricultural soils.
- Soil pH (pH in H2O and KCl solution). The pH (potential of hydrogen) determines the degree of adsorption of ions (H+) by soil particles and indicates whether a soil is acidic or alkaline. It is the main indicator of nutrient availability to plants, influencing the solubility, mobility, availability and other inorganic constituents and contaminants present in the soil. The pH value in soil ranges from 3.5 (very acidic) to 9.5 (very alkaline). Very acidic soils (<5.5) tend to have high and toxic amounts of aluminum and manganese. Very alkaline soils (>8.5) tend to be dispersed. The activity of soil organisms is inhibited in very acid soils and for agricultural crops the ideal pH value is 6.5.
- Organic carbon density (SOCD; kg/m^3). It is a common index to characterize Soil Organic Carbon storage [22], accurate prediction of SOCD has great importance.

2.3. MSMx web service

The MSMx soil database comprises an extensive dataset, hosting 7,892 million records per variable. The cumulative size of this substantial database amounts to 86,812 million data entries. To access this service, you can visit the National Remote Sensing and Modeling Laboratory portal at https://clima.inifap.gob.mx/lnmysr/DatosIndirectos/MSMx (Figure 1).

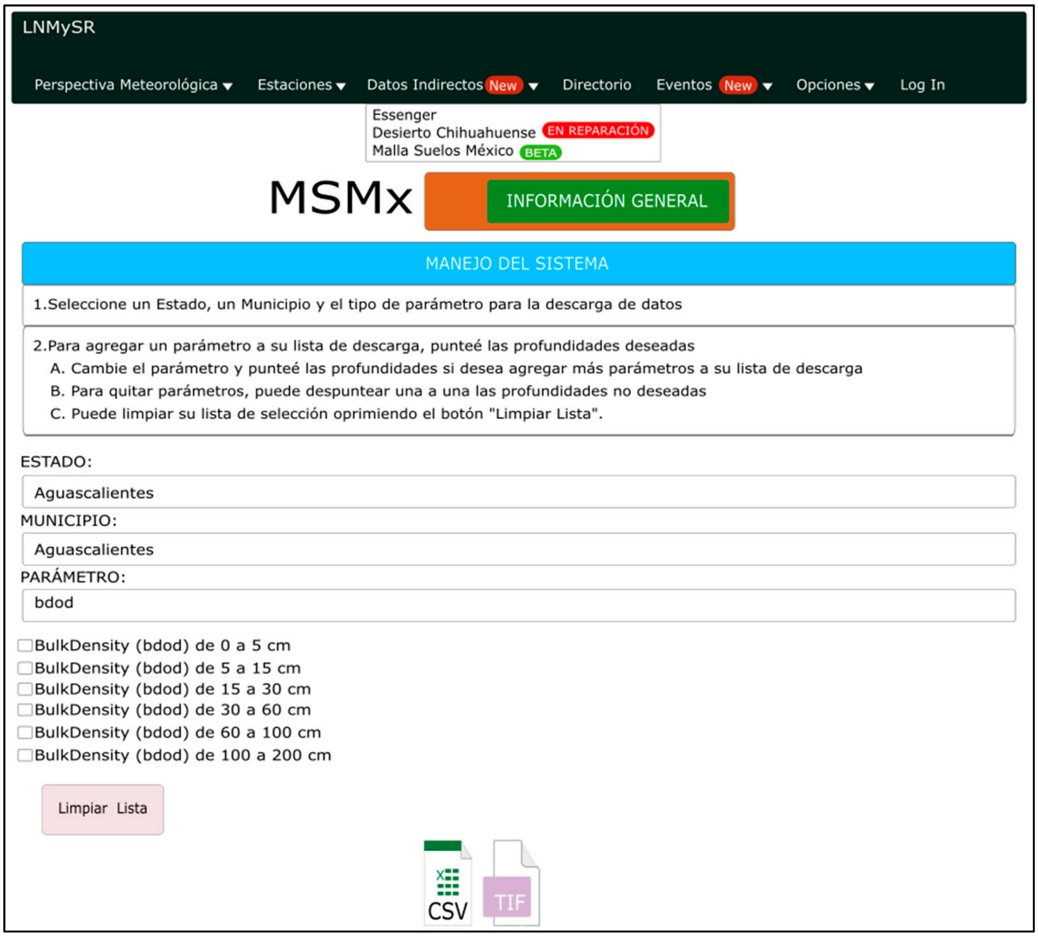

Figure 1. Web service MSMx; contextual menu.

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Figure 1 showcases the user-friendly interface of the MSMx web service with a simplified diagram outlining the hierarchical query process. Utilizing common expressions like <<connect by>>, <<with recursive>> to demonstrate hierarchization intricacies is beyond this manuscript's scope, but it's crucial to emphasize the robustness of the web service in these terms.

The MSMx dataset operates within an SQL environment, leveraging the capability to execute hierarchical queries. SQL enables the programming of queries for filtering hierarchical structures, commonly resembling tree-like formats. Such structures are employed to model relationships like parent-child dynamics or hierarchies such as organizational charts, file systems, or geographical locations.

While delving into the technicalities of expressions like <<connect by>>, <<with recursive>> exceeds the scope of this manuscript, it's crucial to note the robustness of the web service in this regard. Figure 1 offers a simplified representation of the hierarchization process, illustrating the selection by entity and the user's ability to choose the output format.

2.3.1. Key benefits of the MSMx web service include

- Responsiveness: The service is adaptive, ensuring a seamless user experience across various screen sizes.
- User Empowerment: Users can dynamically filter data hierarchically by State, Municipality, soil parameter, and depth, offering a personalized exploration.
- Data Download Options: The service facilitates subsequent data management by allowing the download of filtered data in two formats: plain text (including the coordinate pair of each centroid) and GeoTIF image format. This flexibility caters to diverse user preferences and specific needs.

The decision to export data in plain text or grid format depends on factors such as data complexity, user requirements, and the intended use of spatial data. Both formats have their merits, and the choice should align with the practical aspects of data handling and analysis within a geographic information system environment.

The following are some of the advantages and disadvantages of these formats.

2.3.2. Plain text; (CSV, GeoJSON, TXT): Pros

- Human-Readable. Plain text formats are human-readable, making it easy for users to inspect and understand the data without specialized software.
- Versatility. Plain text formats are versatile and can be easily opened and processed by a wide range of tools, including spreadsheet software and text editors
- Interoperability. Plain text formats are widely supported across different platforms and systems, promoting interoperability.
- Lightweight. Plain text files tend to be smaller in size compared to some binary formats, making them suitable for sharing over networks or via email
- Ease of Integration. Data in plain text formats can be easily integrated into various applications and workflows.

2.3.3. Plain text; (CSV, GeoJSON, TXT): Cons

- Limited structure. Plain text formats may lack the structured organization and metadata support compared to dedicated GIS file formats, potentially limiting advanced GIS functionality.
- Data Redundancy. In some cases, plain text formats may require redundant information (e.g., repeating coordinate values for each point), leading to larger file sizes.
- Limited Spatial Indexing. Plain text formats may not efficiently support spatial indexing, which can impact the speed of spatial queries on large datasets.

2.3.4. Grid Data Format (GeoTIFF, NetCDF, BIL, ASCII, etc): Pros

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- Spatial Indexing. Grid formats provide a natural way to spatially index and organize data. Each cell in the grid corresponds to a specific spatial region, making it easier to locate and retrieve data associated with particular locations.
- Efficient Spatial Queries. Grid-based spatial indexing allows for efficient spatial queries. Point data retrieval within a specific grid cell or a range of cells can be faster than scanning through the entire dataset, especially when dealing with large spatial datasets.
- Regular Structure. Grids have a regular and structured layout, which simplifies certain types of spatial analysis. Operations like nearest neighbor searches or spatial aggregation can be more straightforward within a grid structure.
- Parallel Processing. Grid-based data can be conducive to parallel processing, particularly in distributed computing environments. Analyzing data cell by cell allows for parallelization of certain spatial operations, leading to improved processing efficiency.
- Visualization. Grids provide a convenient structure for visualizing spatial data. Grid cells can be represented as pixels in raster images, allowing for easy visualization and interpretation of spatial patterns.

2.3.5. Grid Data Format (GeoTIFF, NetCDF, BIL, ASCII, etc): Cons

- Data Sparsity. In a grid format, cells may cover areas where no point data is present, leading to data sparsity. This can result in storage inefficiency and computational overhead when processing empty cells.
- Loss of Precision. Representing point data within grid cells may result in a loss of precision, especially when points are densely distributed. Smaller grid cell sizes can mitigate this issue, but it may lead to increased computational demands.
- Inflexibility for Irregular Distributions. Grids may not be well-suited for handling point data with irregular distributions. In cases where points are clustered or follow a specific pattern, a grid structure may not adapt well to the underlying spatial characteristics.
- Grid Size Sensitivity. The choice of grid cell size is crucial. If the grid cells are too large, there may be a loss of spatial detail. On the other hand, if cells are too small, it may result in an excessive number of cells and increased computational complexity.
- Boundary Effects. Grids introduce boundary effects, where points near the edges of cells may not be accurately represented. This can impact the results of spatial analyses, especially when considering points near grid cell boundaries.
- Dynamic Data. For dynamic or frequently updated datasets, maintaining a grid structure can be challenging. The regularity of grids may not adapt well to changes in point data distribution over time.

While grid data formats offer advantages in terms of spatial indexing, efficient queries, and parallel processing, they may not be the most suitable representation for all types of point data. The choice between grid-based and other spatial data structures depends on the nature of the data, the type of spatial analysis required, and the specific use case. In some scenarios, hybrid approaches that combine grid-based and point-based representations may provide a balanced solution.

2.4. Considerations

- Data Type. The type of spatial data (vector or raster) and the specific use case influence the choice of format. Vector data may be more suitable for plain text, while raster data often works well with grid formats.
- Usability. Consider the technical proficiency of the end-users. If the users are comfortable with GIS software, a grid format may be more appropriate. If simplicity and wide accessibility are priorities, a plain text format might be preferred.
- Interoperability Requirements. Consider the interoperability requirements with existing systems and workflows. If the data needs to be integrated into GIS software, a grid format may provide better support for advanced GIS functionality.
- Metadata Requirements. If detailed spatial metadata is crucial for understanding and interpreting the data, a grid format with metadata support may be preferred.

2.5. Conclusions

The Mexican Soils Mesh (MSMx) web service stands out for its programmatic capacity to manage large databases and its synchronization with the SQL language. This work environment simplifies the task of users by allowing them to download only the variables needed for their studies and at the relevant spatial scale.

The programmatic structure of MSMx is aligned with a responsive and intelligent web design. It has the ability to resize and adapt its content according to the screen size of the device. In addition, it can incorporate satellite programming modules to manage the extensive soils database. These features improve query speed, optimize development times and make it a manageable and highly cost-effective project.

3. Methods

Managing and working with raster data efficiently requires a combination of careful planning, appropriate storage solutions, and leveraging available technologies to overcome the challenges associated with data size and complexity. The original soilgrids raster are available online as a 1° x 1° image.

The downloading process implied the next main stages:

- Data Download. Because of the spatial coverture of the original dataset, we have to download specific subsets of data.
- Cloud-Based Storage. Hard disk-based storage solutions for managing large raster datasets was adopted.
- Compression Techniques. A compression technique was not applied for onot compromise data quality.
- Data Management Practices. An effective data management practices, including archiving, organizing, and documenting raster datasets was applied. This ensures efficient use of disk space and facilitates easy retrieval.
- Upgrade Hardware and Network Infrastructure. If feasible, consider upgrading hardware components, such as increasing RAM or using a faster internet connection, to enhance the performance of downloading and processing raster data.
- The mosaicking technique was applied to get the spatial continuous raster.
- The convert tool of GDAL was applied in order to export the raster structure yo plain text. This action did increase in 76 % the size of the file.

4. User Notes

The deployment of the Soil Mesh Mexico (MSMx) web service effectively addresses a recurring requirement for researchers, producers, and academics. This service stands out due to its incorporation of advanced programming tools, offering a high degree of flexibility for the efficient management of the extensive database it encompasses. The noteworthy feature of this service is its programmed capability to export the database in two interchange formats, empowering users to seamlessly integrate and manage it within geographic information systems.

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Data Availability Statement: We encourage all authors of articles published in MDPI journals to share their research data. In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Where no new data were created, or where data is unavailable due to privacy or ethical restrictions, a statement is still required. Suggested Data Availability Statements are available in section "MDPI Research Data Policies" at https://www.mdpi.com/ethics.

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