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AgStat: Automated variable-rate prescription generation for precision agriculture
AgStat: Generación automática de prescripciones de tasa variable para agricultura de precisión

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Technological innovation: The variable-rate prescription generation process is automated and simplified for the user.

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Resumen

La adopción de las tecnologías de información intensiva (IITs) para agricultura de precisión (mapeo de suelos, análisis estadístico, generación de prescripciones) es bajo porque las IITs requieren que el usuario posea conocimientos y habilidades especializados. Esto a diferencia de las tecnologías de conocimiento encarnado (EKTs) cuya adopción es mucho mayor (autoguiado, corte de sección, entre otras) ya que el operador no necesita ser un experto para usarlas. Muchos de los usuarios de las IITs no tienen suficiente familiaridad con las tecnologías de la información. Para motivar a dichos usuarios a beneficiarse de las IITs se requiere de aplicaciones que sean fáciles de usar. Este trabajo presenta “AgStat” una aplicación que incorpora un algoritmo para generación automática de prescripciones de tasa variable. El sistema calcula la tasa adecuada de un insumo para zonas individuales de un campo considerando las necesidades del cultivo y la distribución espacial de variables de interés (ej. Nitrógeno). AgStat fue diseñada para proveer a los productores, investigadores y asesores con una herramienta fácil de usar para realizar procesamiento automático de datos. La aplicación fue desarrollada en lenguaje Python e incorpora mapeo de suelos, visualización de datos y un algoritmo automático para generar prescripciones de tasa variable

(VRPG) para aplicación de nitrógeno. La VRPG es lograda gracias a modelos matemáticos y genera un archivo “shape” que puede ser guardada en una memoria externa. Se presenta un caso de estudio en el que las prescripciones generadas para aplicación de urea, tanto en forma granulada como mediante fertirrigación representaron 34.6% y 67.3% de ahorro, respectivamente en comparación con la estrategia original del productor. AgStat provee las guías para toma de decisiones de una IIT sin necesitar que el usuario sea un especialista en sistemas de información geográfica o un asesor agronómico experto.

Palabras clave: Prescripción agronómica, Agricultura de precisión, Mapeo de variabilidad espacial, Aplicación fácil de usar.

Abstract

The adoption rate of information-intensive technologies (IITs) for precision agriculture (soil mapping, statistical analysis, prescription generation) is low because IITs require the user to have specialized knowledge and skills. Unlike embodied knowledge technologies (EKTs), whose adoption rates are much higher (autosteering, section control, among others), the operator does not need to be an expert to use them. Many potential IIT users have low information technology literacy, and to encourage them to use and benefit from software programs, easy-to-use applications are needed. This work introduces “AgStat,” an application that incorporates a fully automated prescription-generation algorithm capable of computing the appropriate input rate for individual field zones based on the needs of the crop and the spatial distribution of the variable of interest (i.e., nitrogen). AgStat was designed to provide farmers, researchers, and advisors with a user-friendly system to perform automated data processing. The application was developed in Python language and incorporates soil mapping, data visualization functionalities, and an automated variable-rate prescription generation (VRPG) algorithm for nitrogen application. VRPG is achieved through mathematical models and results in a ready-to-use ESRI shapefile that can be exported to an external USB drive. A case study is presented in which the prescriptions generated for urea application—both in granulated form and through fertigation—represent savings of 34.6% and 64.3%, respectively, compared with the farmer’s original strategy. AgStat provides insights for decision-making in an IIT without requiring the user to be a specialized geographic information systems operator or an expert agronomic advisor.

Keywords: Agronomic prescription, Precision agriculture, Spatial variability mapping, user-friendly application.

Introduction

Agricultural practices are constantly evolving according to the challenges faced by humanity and the knowledge and technologies available (Khana & Kaur, 2019). The increase in population, high fertilizer prices (Beghin & Nogueira, 2021), the need for sustainable agricultural practices, and a constantly growing production demand have led to Precision Agriculture Technologies (PATs). PATs rely on data processing to help farmers optimize their resources and increase their productivity via site-specific management (Bhakta et al., 2019).

Barnes et al. (2019) cited numerous studies that have classified PATs into two major categories based on the level of interaction and knowledge required to operate them: Embodied Knowledge Technologies (EKTs) and Information Intensive Technologies (IITs). Autosteering and section control are good examples of EKTs. They have been proven to be adopted at a considerably higher rate than non-automated technology since they do not need specialized skills or technical knowledge once installed. On the other hand, IITs, like data geoprocessing and soil characterization, need more knowledge and human capabilities to benefit from them (Erickson et al., 2018).

Geographic information systems (GIS) are standard tools for information-intensive tasks, often operated by formally educated specialists (Ramezan et al., 2024; Serame & Afuye, 2024). This type of software offers many tools and options, and proper operation requires an understanding of the processing that can be done with it. Users unfamiliar with GIS and other statistical software can feel intimidated or frustrated when presented with a user interface that offers many options and tools they do not know or understand (Zhu et al., 2021; Zelazowska, 2019).

Many potential PATs users are senior citizens who lack an information technology affinity. An easy-to-use and engaging user interface (UI) can enable this group of people to use and benefit from software applications (Nugraha et al., 2019). UI and user experience (UX) design significantly impact technology adoption, satisfaction, and user loyalty (Kim & McFadden, 2020). Darejeh & Singh (2013), later cited by Fu et al. (2022), compiled UI/UX solutions for users with low computer literacy: clear and straightforward navigation paths, reduced number of features available at any given time, avoidance of complicated terminology, use of similar functions for different jobs, an available user guide and help in the software, among others.

Addressing the need for user-friendly systems for farmers, some applications have been developed by both the scientific community and private companies.
For example, Albornoz et al. (2018) and Paccioretti et al. (2020) designed and developed user-centered/easy-to-use applications for automatic management zone delineation via fuzzy K-means clustering, considering multiple data layers. The system developed by Albornoz et al. (2018) was programmed to generate an ESRI shapefile as the last step in its processing sequence. Nevertheless, the user manually enters the rate values for each management zone, so technical knowledge or access to an expert is required. Similarly, commercial software like Operations Center (John Deere, 2023), NEXT Farming Live (NEXT Farming Live, 2023), or Farm Works (Trimble Agriculture, 2018) requires the user to input or select the rate values manually.

The aforementioned literature describes several software tools for generating VRT maps, but it often overlooks that many farmers are not trained to use these geospatial analysis systems. To address this problem, this work focused on the design and development of an application capable of using mathematical models to calculate input rates from soil and/or crop information and to automatically produce ready-to-use VRT prescription files. To achieve this objective, an algorithm was developed to automate the VRT file creation based on previously calculated rate values. Additionally, a graphical user interface was designed following the usability guidelines by Darejeh & Singh (2013) to ensure accessibility for senior farmers. Moreover, in the case study presented in this paper, AgStat automates the prescription generation process via expert-approved models (Stanford, 1973) that

predict the optimum nitrogen rate for each specific site in the field. Then a ready-to-use prescription ESRI shapefile is exported by the system. This methodology gives AgStat the advantages of EKTs while being an IIT. It does not require the user to be proficient in software/GIS operation or have the agronomic knowledge of an expert advisor to perform essential precision-agriculture (PA) data collection, processing, and variable-rate prescriptions.

This first version of the application "AgStat" was developed to provide advisors, researchers, and farmers with an integral/easy-to-use tool to perform fully automated agricultural data processing, particularly prescription map generation, thereby facilitating the PAT transfer from advisors to farmers and improving their resource-use efficiency as a result (Karunathilake et al., 2023).

Materials and methods

Application

AgStat application was developed in Microsoft Windows OS with Python programming and open-source libraries; its graphical user interface was designed and implemented with the PyQt5 package (Willman, 2021). Optimized data processing was carried out by NumPy (Harris et al., 2020; Nishant et al., 2020) and Pandas packages (Reback et al., 2022). Raster processing algorithms were built with the GDAL library (GDAL/OGR contributors, 2022; Hu et al., 2021; Lemenkova, 2020b; Ma et al., 2020; Appel et al., 2018); vector data processing was achieved with GeoPandas (Jordehl et al., 2020), and the results were plotted with Matplotlib and Seaborn packages (Wiskom, 2021; Lemenkova, 2020a; Hunter, 2007).

AgStat organizes data into client profiles containing farms, fields, and agricultural cycles. The user must specify that information to access files, visualizations, or update the database. The visual interface guides the user step by step in every process, showing only the essential elements needed; on every screen is a help icon to support the user during the operations. The layout and colors chosen were used consistently in the UI design to facilitate navigation and help the user benefit from the system.

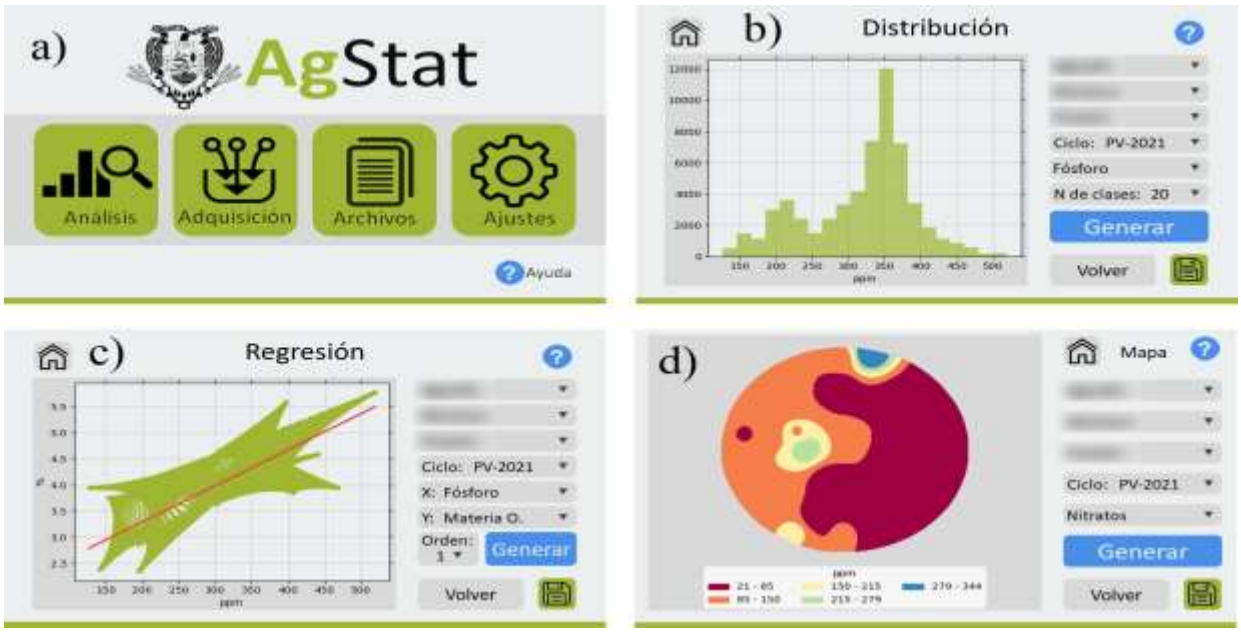


Figure 1. AgStat's screenshots: a) Main menu, b) Histogram, c) Regression plot, d) Nitrate distribution map.

Algorithms

Data Acquisition Algorithm (DAA):

Data can be acquired to the system through a user-provided comma-separated-values (CSV) file with Latitude, Longitude, and variable fields with information on soil or crop parameters. Optional data preprocessing is offered; if the user considers that the provided data is clean, properly interpolated, and ready to be used, preprocessing may be skipped (Figure 2a). The algorithm then proceeds to resample the values to a 2 x 2 m regular grid (RG) via the nearest-neighbor technique (Shannon et al., 2020) and adds a column with the new variable's values to the database. The purpose of resampling the data is to obtain a high-resolution common grid for all data points, allowing the algorithms to easily perform operations that involve two or more variables.

If preprocessing is needed, the DAA removes the data points outside the 5th and 95th percentiles to remove possible outliers and obtain a more generalized dataset. Then, the system automatically decides which interpolation algorithm to use to assign the new variable values to the RG. If the number of data points is less than 100, then IDW interpolation is used (Setianto & Triandini, 2015); when the database has more than 100 observations, moving-average interpolation (Michelon et al., 2019) is performed. The goal of this interpolation step is to create a smooth surface that forms relatively large polygons when classified by range. Both interpolation algorithms used were obtained from the "GDAL.grid" method (Lemenkova, 2020b).

After the interpolation is finished, the database is updated with the new variable. The data are classified into five evenly spaced ranges to generate a single-variable map. This classification method is fixed in this prototype for user-interface simplification and facilitates map interpretation by displaying two high ranges, two low ranges, and a middle range. The map is stored as an ESRI shapefile that the user can later access in the "visualization–maps" section of the app (Figure 3). This processing is performed for every soil or crop parameter in the CSV file provided by the user.

Prescription Generation Algorithm (PGA):

This algorithm was designed to provide the user with an intuitive way to generate variable-rate prescriptions (Figure 2b, Figure 3). The user interface displays the model for which the selected field has the necessary data to operate.

Nitrogen Rate Model (NRM): Considers the nitrogen extraction needs of the crop according to a yield goal, the nitrogen present in the soil, the nitrogen assimilation efficiency of the crop, the fertilization method, and the fertilizer to optimize the nitrogen rate for each specific site. The rate is obtained with the following equation adapted from Stanford (1973).

$$NitrogenRate(kgha^{-1}) = \frac{(Yg \times N_e) - ((N_m + N_i + N_r + N_o) \times Ef_N)}{Ef_{fert}} \textbf{ (Eq. 1)}$$

Where: Yg is the yield goal of the crop in t ha-1, Ne is the nitrogen extracted by yield ton for a given crop, Nm is the mineralized nitrogen in the soil, Ni is the inorganic nitrogen in the soil's profile, Nr is the residual nitrogen on the soil, no is the organic nitrogen in the soil, EfN is the crop's nitrogen assimilation efficiency, and Effert is the fertilization method's efficiency. Once the model is selected, the application predicts a rate for each data point and then classifies the continuous surface in nine evenly spaced

values to form nine management zones. This classification was designed to allow a relatively smooth change between different rates by maintaining consistent rate changes over the field. Next, the resulting ESRI shapefile is plotted. Finally, the system helps the user export the ESRI shapefile into an external USB drive to carry the prescription to a variable rate machine in the field.

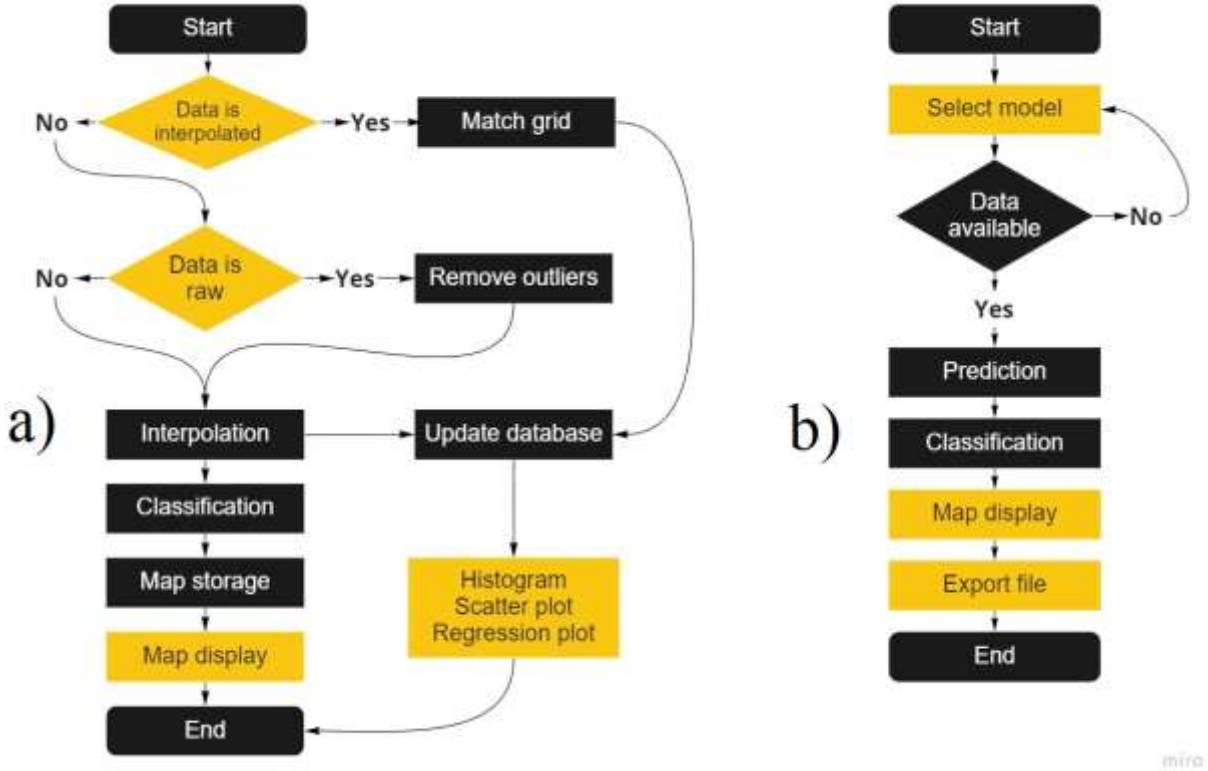


Figure 2. Flow charts for a) Data Acquisition Algorithm and b) Prescription Generation Algorithm.

Case study:

Georeferenced data from a 21-ha center-pivot silage corn field in Mexico (21.75744N, 102.309762W) was used to test the algorithms. Soil samples were taken at a rate of 1 sample per 0.84 ha. Samples were analyzed in a specialized laboratory (Fertilidad de Suelos S. de R.L.) in October 2021. A client profile was created in AgStat to store the pertinent files; farm, field, and agricultural cycle were also added. Also, an ESRI shapefile containing the field's boundaries was stored in the field's directory. The DAA processed a CSV file containing the 25 georeferenced soil analysis results, resulting in multiple maps and an RG database. Figure 1d shows the spatial distribution of the nitrate concentration.

A yield goal of 24 t ha-1 of dry-matter corn was established, as it is a common value for high-yielding silage corn in the area; this goal was also supported by the laboratory's analysis. The considered nitrogen extraction need for the silage corn crop was 12 kg t-1 (Stanford, 1973), with a nitrogen assimilation constant of 60%, and two application scenarios were considered: 40% application efficiency for granulated fertilizer and 80% with fertigation via center pivot. The user only needed to specify the model, crop, yield goal, fertilizer, and application method. The

fertilizer selected to apply nitrogen was urea (46,00,00). Nitrogen extraction needs, fertilizer's nitrogen content, and efficiency constants are stored in the system, so the user does not need to memorize that information.

With the previous parameters, variable-rate urea prescriptions (Figure 3) can be generated and exported as an ESRI shapefile to an external USB drive.



Figure 3. Prescription processing screens. a), b) & c) Client, crop and model selection, d) Data confirmation, e) Prescription map, f) Prescription export, g) Successful export notification.

Results and discussion

AgStat was developed as an open-source tool and can be deployed on any system that supports the Python programming language. For all data operations, the user must specify the client, farm, field, and agricultural cycle of interest. That selection remains the same across the different sections of the application (visualization, prescription generation) unless the user selects another profile, farm, field, or cycle.

Data processing by DAA resulted in maps with different spatial classes according to each variable. In addition, ready-to-use prescription files were generated quickly and easily with PGA (Figure 3), facilitating the task for the user since the technical information and methodologies are embedded in the system. The automatically prescribed rates (Table 1) based on Stanford's model (Stanford, 1973) represent 34.6% total savings in fertilizer for scenario one and up to 67.3% for scenario two, both compared with the farmer's previous strategy of applying granular urea to the field at a fixed rate of 650 kg ha-1.

Nonspecialized users can feel overwhelmed and confused by the enormous options and tools that a GIS can offer, so this application was designed only with the essential tools that precision agriculture end users would need. The app's information architecture was designed intuitively, with no more than four options per menu to ease the user's decision-making and navigation processes (Darejeh & Singh, 2013). This work is aimed at creating an integral/easy-to-use tool to collect, visualize, and process agricultural data without requiring the user to possess advanced skills in geoprocessing software.

Automatic data processing applications for precision agriculture have been developed in recent years. Some are designed to define management zones and their statistical insights (Albornoz et al., 2018; Paccioretti et al., 2020), and generate thematic maps, like AgDataBox (Michelon et al., 2019; Borges et al., 2020; Dall'Agnol et al., 2020). In general terms, the previously mentioned applications were designed to transform raw data into meaningful information layers to support farmers' management decisions. However, only GeoFis (Leroux et al., 2018) and the system developed by Albornoz et al. (2018) take the data to the decision layers.

GeoFis enables specialists to incorporate their knowledge via expert rules to process data layers and support decision making. This system allowed the GeoFis developers to create a 'risk of having sub-optimal practices' map of a vineyard. On the other hand, the application created by Albornoz et al. (2018) automatically generates ESRI shapefiles that contain the polygons of management zones and offers a friendly interface to enter the input rate value for each zone. The latter methodology has great flexibility since any input can be prescribed using the same interface. However, the user needs to have specific technical knowledge or have access to an expert to decide the proper input rates.

This work proposes a fully automated prescription-generation process that decides the appropriate input rate for each site, based on the needs of the crop and the spatial distribution of the variable of interest (i.e., nitrogen). The AgStat user does not need to be an expert to generate variable-rate prescriptions. Instead, the user only enters the necessary information into the system and lets the application predict the rates, classify them into management zones, and export a ready-to-use shapefile. However, this approach is limited by the models and embodied knowledge available in the system.

A nitrogen-only macronutrient prescription was adequate for this case study since the

application of phosphorus and potassium was not advised due to high concentrations of those elements in the field. Nevertheless, the actual effect on crop yield due to the prescriptions generated by the system needs to be quantified to fully validate the models. Additionally, the adequate execution of the prescriptions would depend on how precisely the variable-rate machinery responds to rate changes. After evaluation in the field, the prescription zoning can be adjusted to optimize input application.

For now, the developed PGA outputs single-variable prescriptions (nitrogen). This approach has the advantage of managing each input precisely. However, it is limited when more generalized management zones need to be created (i.e., Fuzzy K-Means) to apply more than one input in one machinery pass (i.e., variable-rate NPK fertilization). With future research, numerous models can be developed and tested to predict optimum rates for a variety of inputs for different crops and conditions, including NPK and micronutrient formulas. Adding those models to the system would favor the adoption of information-intensive technologies since it would not be very knowledge-demanding and would result in input savings and environmental benefits. The average precision agriculture user could take advantage of such tools with simple training.

Table 1. Urea rates automatically prescribed for each zone on both scenarios.

Zone	Surface (ha)	Scenario 1: Granulated		Scenario 2: Fertigation	
		Prescribed urea rate (kg ha^{-1})	Total urea (kg)	Prescribed urea rate (kg ha^{-1})	Total urea (kg)
1	5.2	0	0	0	0
2	2.8	138	386.4	69	193.2
3	1.3	278	361.4	139	180.7
4	1.7	418	710.6	209	355.3
5	3.5	558	1953	279	976.5
6	2.8	698	1954.4	349	977.2
7	3.4	838	2849.2	419	1424.6
8	0.8	978	782.4	489	391.2
9	0.2	1118	223.6	559	111.8
Total	**21.7**		**922**1		**4610.5**

Conclusions

This first version of AgStat was developed as an open-source, low-cost PA tool for non-expert users, focusing mainly on automated prescription map generation. The system embodies the GIS operation skills and technical criteria a PA specialist needs to perform some of PA's fundamental operations, broadening access to PATs and making them more attainable for small and medium-scale producers while enhancing their capacity for data-driven decision-making. Nitrogen prescriptions were generated successfully in an automated manner; however, the prescription effect on yield and costs still requires validation across a wider range of field environments. The case study presented focused solely on nitrogen prescription, and future research, model testing, and development are required to improve the system's capabilities and add more advanced functionalities to an intuitive user experience. Upcoming developments aim to incorporate modules for other

nutrients, integrate yield datasets, and enable real-time analysis of field information. The authors hope that products like AgStat and similar applications help increase IIT adoption rates by PA users, leading to more sustainable and productive agricultural systems.

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AgStat source code can be found at https://github.com/andrescadenadi/AgStat. This application can run on any platform with Python 3.7 or a later version installed. For its development, the following library versions were used: GDAL 3.2.1, GeoPandas 0.10.2, Matplotlib 3.4.2, NumPy 1.20.3, Pandas 1.3.3, PyQt 5.15.2, and Seaborn 0.11.2.

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