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Role of Precision Agriculture in Mitigating Black Sigatoka in Banana Cultivation Under Climate Change: A Review and Bibliometric Analysis

Rol de la agricultura de precisión en la mitigación de la sigatoka negra en cultivos de banano bajo cambio climático: Una revisión y análisis bibliométrico

Luis Miguel Torres Ustate[1];
Nelson Virgilio Piraneque Gambasica[2];
Martha Ligia Castellanos Martínez[3]

[1]Universidad de La Guajira
Riohacha-Colombia,
lmigueltorres@uniguajira.edu.co
[2]Universidad del Magdalena
Santa Marta-Colombia,
npiraneque@unimagdalena.edu.co
[3]Universidad de La Guajira
Riohacha-Colombia,
mlcastellanosm@uniguajira.edu.co

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Abstract

Black Sigatoka, caused by the fungus *P. fijiensis*, is the most severe disease that affects bananas *(Musa spp).* Research has projected increases in disease severity in response to climate change and variability, highlighting the need to analyze the relative contributions of climate change and immediate responses to their effects on these crops. This study aimed to analyze the influence of climate variability and spatiotemporal variability of soil and climatic conditions on Black Sigatoka. In addition, it was evaluated the use of geostatistical, geomatics, remote sensing, and geographic information systems techniques for disease detection over the past 30 years. A systematic review of 156 articles was conducted using bibliometric analysis, considering descriptive statistics and bibliometric mapping using VOSviewer. The results showcased geostatistical methods used to measure Sigatoka infection in banana crops and identify soil and climatic variables associated with this disease. It is concluded that climate change has the potential to increase Black Sigatoka infection, but precision agriculture could be an effective tool to mitigate the negative impact on banana crops.

Keywords

Banana cultivation, black sigatoka, climate change, crop monitoring, precision agriculture.

Resumen

La sigatoka negra producida por el hongo *P. fijiensis*, es la enfermedad más severa que afecta al banano *(Musa spp).* Existen investigaciones que han proyectado incrementos en la severidad de la enfermedad en respuesta al cambio climático y la variabilidad climática, por lo que es necesario analizar las contribuciones relativas de los cambios del clima y las respuestas inmediatas a sus efectos en este tipo de cultivos. El objetivo de este estudio fue analizar la influencia de la variabilidad climática y la variabilidad espaciotemporal de las condiciones edafoclimáticas sobre sigatoka negra. Además, se evaluó el uso de técnicas geoestadísticas, geomáticas, de teledetección y sistemas de información geográfica para la detección de la enfermedad durante los últimos 30 años. Se adoptó una revisión sistemática de 156 artículos mediante análisis bibliométrico considerando estadísticas descriptivas y mapeo bibliométrico utilizando VOSviewer. Los resultados muestran métodos geoestadísticos utilizados para medir la infección por Sigatoka en cultivos de banano e identifican variables del suelo y climáticas asociadas con esta enfermedad. Se concluye que el cambio climático tiene el potencial de incrementar la infección de sigatoka negra, pero la agricultura de precisión podría ser una herramienta eficaz para disminuir el impacto negativo en los cultivos de banano.

Palabras clave

Cultivo de banano, sigatoka negra, cambio climático, monitoreo de cultivos, agricultura de precisión.

1. INTRODUCTION

Banana (Musa spp.) is one of the most consumed fruits in the world, with a production of approximately 107 million tons per year-1; it is the fourth most crucial food commodity after wheat, rice, and corn [1] and is responsible for feeding more than 500 million people [2], which represents an important economic sector worldwide. The countries with the highest production are India and China, with 33 and 11 million tons per year, respectively [1]; its consumption has spread in those countries located in tropical and subtropical regions (approximately 120 to 130 countries) [3].

It is considered among the first fruits harvested by primitive agriculture and has been present in various cultures and civilizations for centuries; it grows throughout the year with a maturity period of 11 months to 12 months, thrives best in deep and well-drained soils common in the tropics within temperature ranges of 20°C to 30°C and rainfall between 1800 mm and 2500 mm per year, planting is mainly vegetative using sprouts from already established colonies [4]-[6]. However, banana production, mainly for domestic markets, has developed in many subtropical areas under less-than-optimal conditions, where water shortages and high temperatures exacerbate the spread of foliar diseases and reduce crop yields, posing significant challenges in the face of climate change for banana production systems [7], [8].

Pests and diseases are another area of concern, as they can spread and become severe, reducing production, with increased use of biocides with consequent food safety issues [9]- [11]. Black Sigatoka, caused by the fungus *P. fijiensis*, has been identified as the disease that most generates a reduction in banana production in the world [12]-[14]. In general, the evolution of the disease is caused by the dynamics of the export and import of black Sigatoka-infected fruits in addition to favorable climatic and edaphic conditions [12], [15]-[18]. *P. fijiensis* restricts the photosynthetic area of banana leaves. The symptoms initially appear as streaks and, in later stages, can cause complete leaf necrosis. This can result in up to 100 % yield loss, depending on the variety of the cultivar, environmental conditions, and severity of the disease. [2]. It also causes heavy yield drop, early fruit ripening, and significant economic loss [19]- [21].

In Latin America and the Caribbean, Brazil, Ecuador, Guatemala, Costa Rica, Colombia, Mexico, and Peru- in this order sequence -are among the 20 countries that produce the most bananas, representing 26 % of production and the first positions in exports worldwide [1]. However, Latin America is one of the regions that provide an ideal microclimate for black sigatoka (*P. fijiensis*) infection, offering humidity and temperature (minimum 12°C, average 27°C and maximum 36°C) suitable for the development of the disease, which occurs in many banana-producing areas throughout the year [14], [22].

Colombia, in 2021, produced approximately 2.4 million tons of bananas, of which 87 % were exported [1]. About 72236 hectares are destined for banana cultivation [23]. However, worldwide, banana production indistinctly by region, has been affected over time by fungal diseases such as black Sigatoka (*P. fijiensis*) and Fusarium R4T (Fusarium oxysporum f. sp. Cubense race 4 (Foc4)) [24]-[27], which limit the crop, causing considerable yield losses [28]-[30]. Generally, these diseases reproduce in a particular proportion due to increased atmospheric phenomena and climatic variability [15].

Black Sigatoka (*P. fijiensis*) , which originated in Asia, emerged in the late twentieth century and has recently finished spreading throughout banana-growing regions in Latin America and the Caribbean [15]; its spread provides an example of biotic-abiotic migration, where the intersection of biologically and climatically suitable regions, together with increasing international trade and transport have made banana production systems more vulnerable to infection [15]. It is caused by the fungus *P. fijiensis* and is considered one of the most damaging diseases affecting banana crops. Its evolution depends on climatic conditions, and infection initiates in young leaves [31]. This fungus generates total leaf necrosis, sharp drops in production, early fruit ripening, and essential economic loss due to reduced production [2]. Additionally, it is primarily controlled with fungicides, but these treatments not only pose health risks to humans but also come with significant costs [2], [29], [32]-[34].

The establishment and spread of black sigatoka worldwide, while driven by increased banana production and global trade, has also been potentially facilitated by climate change and global warming, which have generated favorable environmental conditions for the germination and increased severity of black sigatoka [15], [35]. In general, the evolution of the disease depends on favorable climatic conditions [31]. However, a direct relationship has also been reported between some nutrients and physicochemical properties of the soil and the severity of black Sigatoka, which reduces the defense response of plants [16], [36].

Detection, monitoring, and early detection of *P. fijiensis* are critical in banana crop production [37], [38]. The traditional detection method for disease management is manual, time-consuming, and labor-intensive, making it challenging to meet export and large-scale development requirements because of the health and production problems associated with the chemicals used [39]. In recent years, accurate and reliable disease detection has been facilitated by highly sophisticated and innovative methods, which relate the spatio-temporal distribution of this disease to environmental factors, such as soil fertility and climate. Modern epidemiology has used geostatistics, a technique that uses GIS, remote sensing and statistics through spatial analysis and the use of sensors to analyze and monitor environmental and agricultural processes [40]-[46]. Geostatistics uses the generated semivariograms to analyze the data and kriging maps to estimate values at unsampled locations with no trend and minimal variance [47].

Despite the use of these technologies, there are still challenges in detecting crop diseases using aerial imagery obtained from manned drones and UAVs or satellites. While many crop diseases can be successfully detected and mapped using satellite or drone imagery, each has unique detection and management characteristics [44]. Much has been studied on black sigatoka (*P. fijiensis*) infection using statistical and geostatistical techniques [2], [12], [16]-[18], [28], [48]-[50]; however, these methodologies have not been explored in detail, there are still gaps in research explaining how edaphoclimatic conditions influence disease. This study emphasizes the use of precision agriculture as a potential solution to the exacerbated effects of black sigatoka, identifying the edaphic properties and climatic variables related to its infection. It addresses aspects linked to the detection, mitigation, and management of black sigatoka. Additionally, it reports on geostatistical methods applied in the experimental design of sampling, which facilitate the subsequent analysis of data, including the visualization of results through maps, thereby providing a better understanding of the disease distribution in the field. In this regard, this review highlights various statistical and geostatistical techniques through spatial analysis and sensors used to study the infection of *P. fijiensis* and its relationship with edaphoclimatic conditions.

2. METHODOLOGICAL ASPECTS

Based on [51], the study was organized into four key stages: 1) data collection, 2) data filtering, 3) data analysis, and 4) conceptual discussion and recommendations for future research. A methodology that integrates systematic review with bibliometric analysis using VOSviewer 1.6.20, a tool designed for informetric, bibliometric, and scientometric analysis

[51], was employed. In this study, co-occurrence analysis was adopted for author keywords, titles, and abstracts, allowing for the visualization of relationships between them and identifying trends and patterns in the literature on *P. fijiensis* infection and its relationship with edaphic conditions, precision agriculture, and SIG approaches. Through VOSviewer, visual maps are generated that help in understanding the current state of research and highlighting areas that require more attention. Figure 1 depicts the framework of the study, including a diagram of the stages and their descriptions.

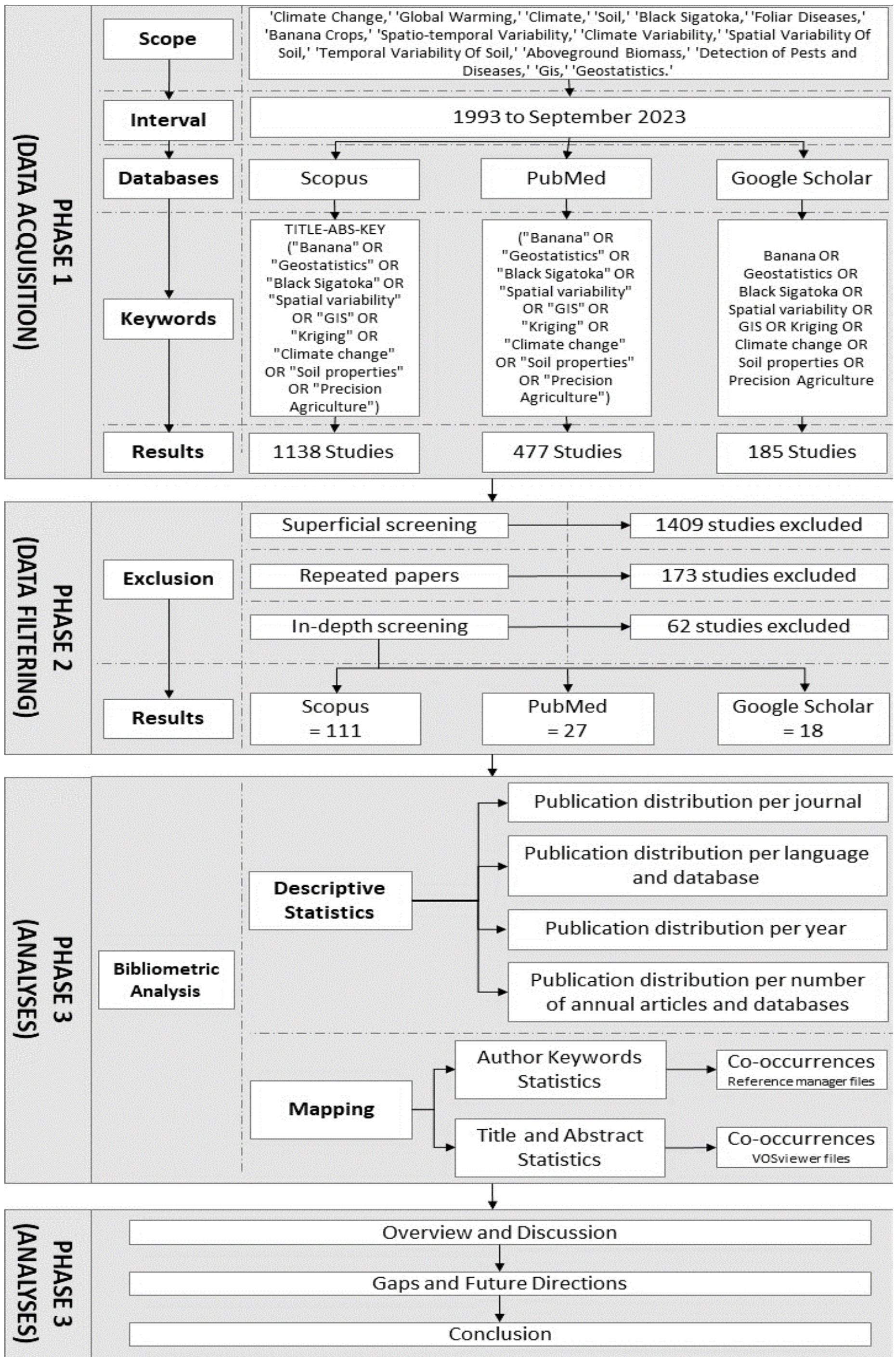

Figure 1. Study flow diagram. Source: own elaboration.

2.1 Literature search strategy

The search utilized bibliographic databases including Scopus, PubMed, and Google Scholar. Titles and abstracts were selected based on these criteria: (1) articles published in peer-reviewed journals, books, book chapters, and conference papers; (2) publications dating from January 1993 to September 2023; this range was selected due to its temporal relevance in addressing the evolution of research on black Sigatoka infection in banana crops, climate change, and GIS approaches over 30 years, encompassing technological advances and preparing for future challenges; (3) no restrictions on the country of origin of the article, provided that most articles were published in English; and (4) those associated with the application of precision agriculture in banana crops.

Because the literature was sourced from three different databases, keyword combinations were meticulously crafted to encompass the study's intended scope and were applied consistently across all databases. The terms used are "climate change", "global warming", "climate", "soil", "black Sigatoka", "foliar diseases", "banana crops", "spatiotemporal variability", "climate variability", "spatial variability of soil", "temporal variability of soil", "aboveground biomass", "detection of pests and diseases", "GIS", and "geostatistics". Multiple combinations of these keywords ensured a comprehensive search of all relevant articles. They were chosen to ensure a comprehensive perspective on automated construction monitoring while allowing for the exclusion of unrelated articles in later stages. In total, 1800 publications were gathered. The entire search syntax and articles collected by databases after applying shallow filters, including publications of the highest relevance and those for which no full text or access was available, are listed in Table 1. For Google Scholar, it was not possible to apply filters.

Table 1. Synthesis of compiled publications. Source: own elaboration.

Database	Keyword combination	Duration	Initial results	Exclusion result
Scopus	TITLE-ABS-KEY ("Banana" OR "Geostatistics" OR "Black Sigatoka" OR "Spatial variability" OR "GIS" OR "Kriging" OR "Climate change" OR "Soil properties" OR "Precision Agriculture")	1993 to September 2023	10056	1138
PubMed	("Banana" OR "Geostatistics" OR "Black Sigatoka" OR "Spatial variability" OR "GIS" OR "Kriging" OR "Climate change" OR "Soil properties" OR "Precision Agriculture")		3776	477
Google Scholar	Banana OR Geostatistics OR Black Sigatoka OR Spatial variability OR GIS OR Kriging OR Climate change OR Soil properties OR Precision Agriculture		-	185
Total publications				1800

2.2 Data filtering

The filtering process was conducted rigorously across all databases. Initially, 1800 publications were identified. A preliminary review of titles and abstracts led to the exclusion of 1409 publications due to lack of relevance. Next, 173 duplicate articles were removed. A thorough reading of the remaining 218 articles resulted in the exclusion of 62 based on their contributions to the study. Ultimately, 156 articles were selected for analysis. A summary of the filtering process is presented in Table 2.

Table 2. Summary of publication exclusion. Source: own elaboration.

Database	Collected studies	Exclusions			Relevant publications
		Surface review	Repeated publications	In-depth review	
Scopus	1.138	838	173	16	111
PubMed	477	415		35	27
Google Scholar	185	156		11	18
Exclusions	0	1409	173	62	
Remaining	1800	391	218	156	156

2.3 Analysis of publications

In this study, bibliometric analysis and bibliometric network mapping were performed for 156 selected publications. The analysis is explained by considering the publications by year, database and language, journal of publication, and network maps of author keywords that are most repeated among all the selected publications. In addition, network maps of the titles and abstracts were created. The full reference records for the chosen papers were imported into the Mendeley reference manager. Additional data were organized in Microsoft Excel for coding and analysis purposes. A standardized form was used to extract the following information: title, author(s), publication year, journal name, authors' keywords, and abstract. Subsequently, the information was migrated to R 4.3.0 for visualization and bibliographic analysis and to VOSviewer 1.6.20 to create a network map.

3. RESULTS AND DISCUSSION

3.1 Characterization of the selected articles

In total, 107 journals published the selected articles; the top 20 journals are shown in Figure 2, with the top seven journals being Catena (6 articles), Sustainability (Switzerland) (5 articles), Plants (5 articles), Science of the Total Environment (4 articles), PLoS One (4 articles), Geoderma (4 articles), and Plant Disease (3 articles) together accounting for 20 % of the selected publications. The journals Catena, Science of the Total Environment, and Geoderma are affiliated with Elsevier; the journals Sustainability (Switzerland) and Plants are affiliated with MDPI; and the journals PLoS One and Plant Disease are affiliated with the Public Library of Science (PLoS) and The American Phytopathological Society, respectively.

The selected articles covered 30 years of publications, mostly in English (Figure 3), showing increasing research interest (Figure 4). The publications are based on strategies to cope with climate change, considering the global expansion of Black Sigatoka and the incidence of climatic and edaphic variables in its occurrence in banana crops. In addition, this study explores the application of geostatistical techniques and GIS in its detection. In this sense, this article provides a comprehensive perspective, highlighting the future challenge of climate change in detecting this disease in banana crops.

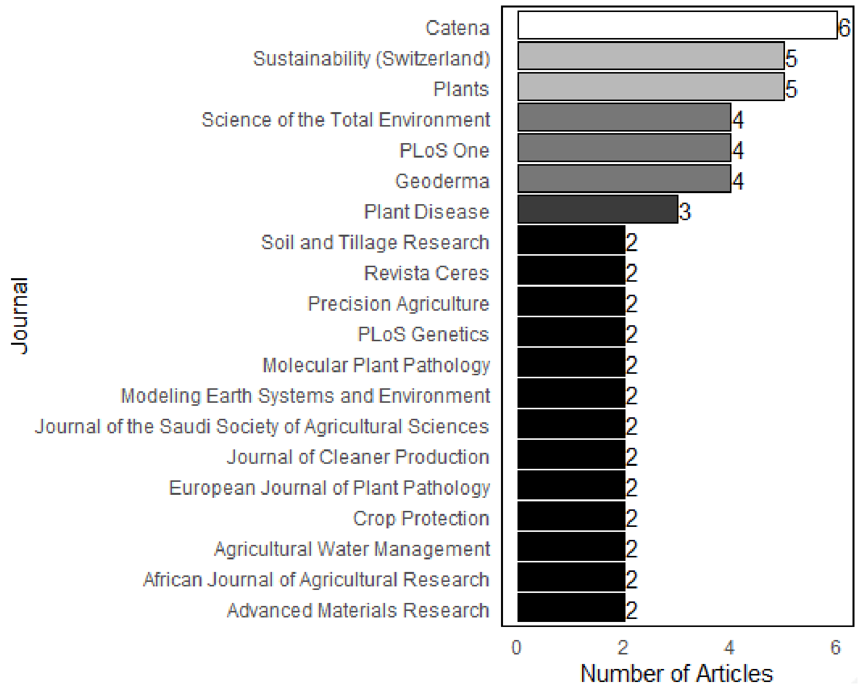

Figure 2. Top 20 journals for selected article publications. Source: own elaboration.

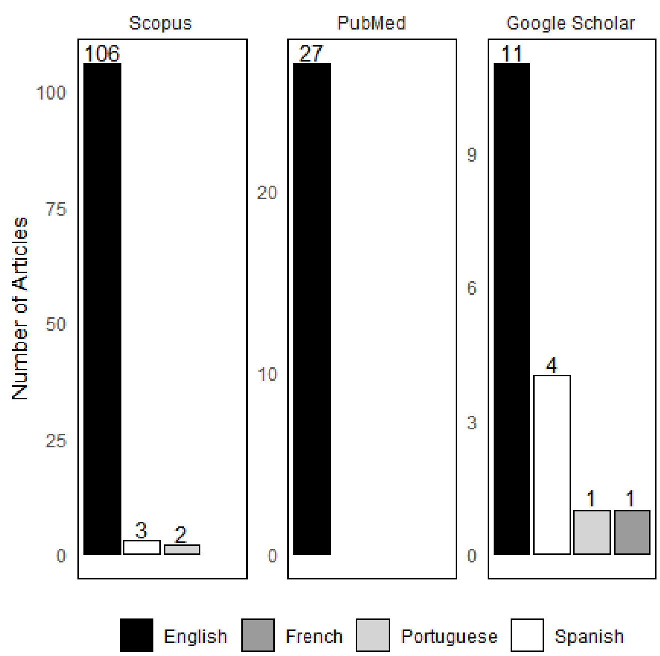

Figure 3. Number of selected articles by language and database. Source: own elaboration.

Figure 5 illustrates the annual distribution of articles published per database from 1993 to September 2023. The trend line indicates that researchers' interest has not waned, as it shows an upward trajectory each year. Overall, Scopus publishes the maximum number of research articles related to the detection of black Sigatoka in banana crops.

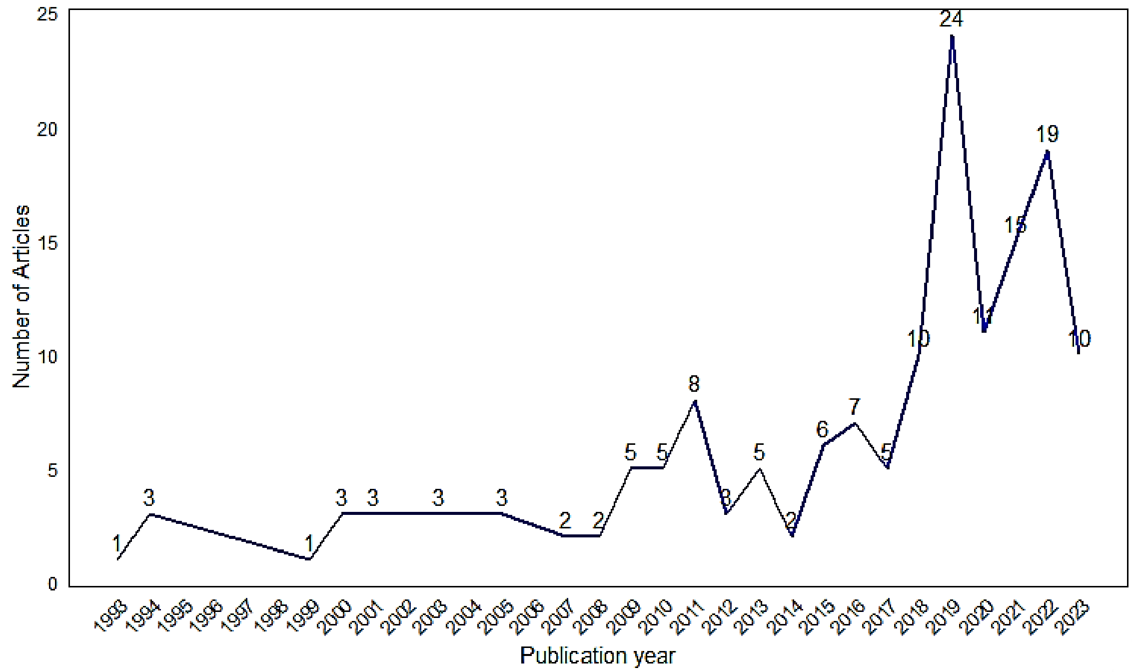

Figure 4. Number of selected articles by year of publication. Source: own elaboration.

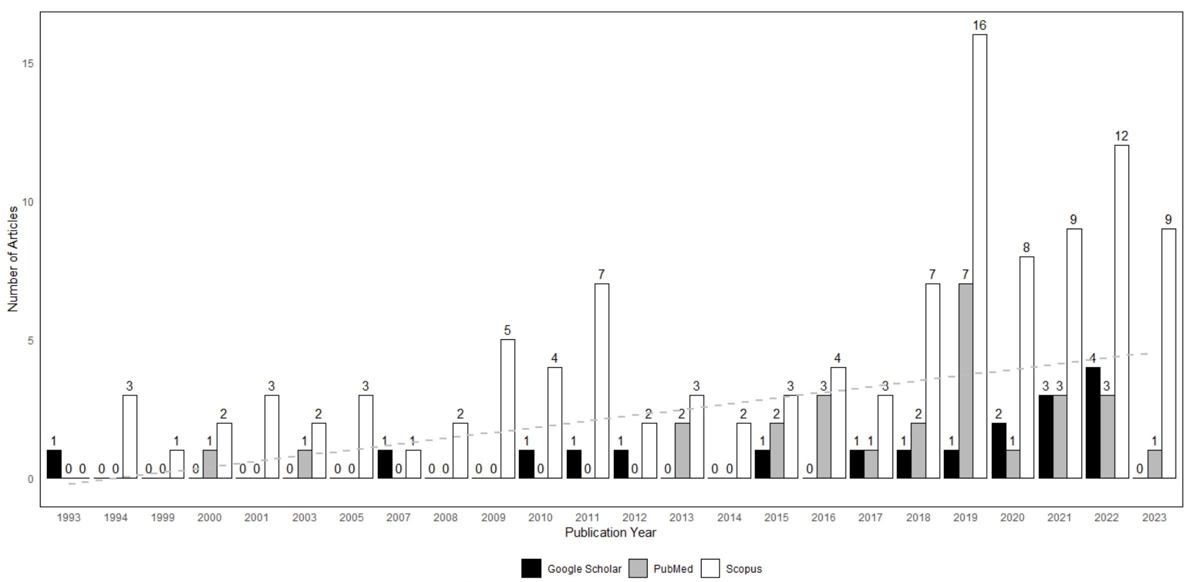

Figure 5. Summary of selected documents by databases. Source: own elaboration.

In this study, a bibliometric mapping was conducted to analyze author keywords and keywords found in the title and abstract of the selected publications. In this regard, a co-occurrence analysis was adopted for these keywords using VOSviewer. The co-occurrence analysis of keywords was conducted in the selected publications (156) by importing a data file in text format to VOSviewer containing only year and author keywords. In the 156 publications, 478 author keywords were identified, with 21 of these meeting the threshold criterion, as the minimum number of occurrences required for a keyword was set at four. The top three author keywords were "Banana" (19.5 %), "Geostatistics" (13.3 %), and "Black Sigatoka" (10.9 %) with occurrence rates of 25, 17, and 14, respectively, for an average publication year of 2018, 2013, and 2017 (Table 3). Figure 6 displays the co-occurrence author keyword mapping network, and a summary of the top 10 co-occurring keywords is presented in Table 3. The keyword mapping is divided into five groups, each illustrating the correlation network among the keywords. However, the terms "Banana" and "Black Sigatoka" show a higher correlation with each other compared to the term "Geostatistics".

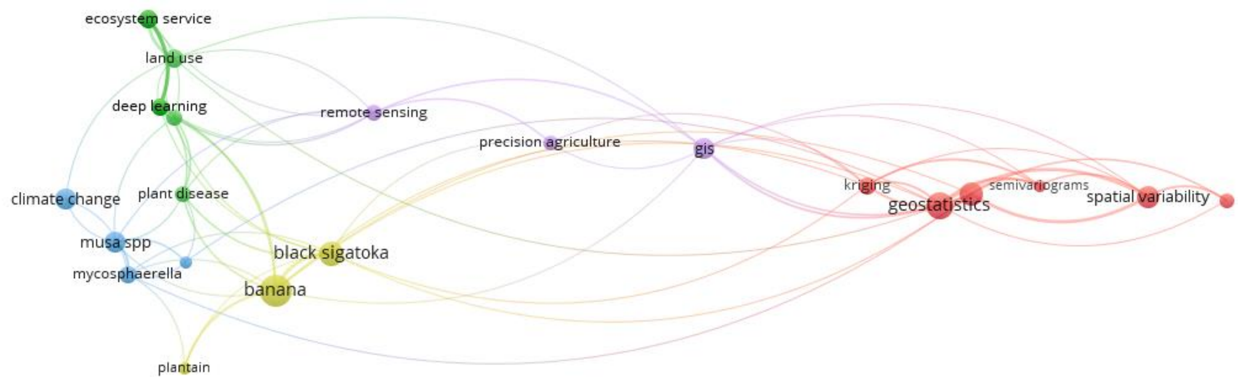

Figure 6. Author keywords co-occurrence mapping. Source: own elaboration.

Table 3. Summary of the mapping of the top 10 author keywords. Source: own elaboration.

Keyword	Occurrences	Percentage	Links	Avg. pub. year
Banana	25	19.5	11	2018
Geostatistics	17	13.3	8	2013
Black sigatoka	14	10.9	9	2017
Soil property	13	10.2	10	2017
Spatial variability	12	9.4	6	2014
Climate change	11	8.6	3	2017
GIS	11	8.6	9	2015
Musa spp	10	7.8	7	2016
Land use	8	6.3	7	2016
Kriging	7	5.5	8	2015

Likewise, bibliometric mapping was performed using several RIS files of the studies that contained the details of the titles and abstracts. Thus, repeated terms or keywords were identified, and co-occurrence mapping was performed. In the 156 publications, 5027 terms were found, with 119 keywords meeting the threshold point, as the minimum number of occurrences for a keyword was set at 10, with the top three terms extracted from the titles and abstracts being the keywords Disease (17.3 %), Soil (16.2 %), and Banana (10.3 %) with occurrence rates of 138, 129, and 82, for an average publication year of 2017, 2015, and 2016, respectively (Table 4). Figure 7 shows the mapping network of keyword-related terms extracted from the titles and abstracts of the selected publications. A summary of the top 10 co-occurring keywords is provided in Table 3. The keyword mapping was distributed into four groups, with each group illustrating the correlation network among the keywords. However, the terms "Disease" and "Banana" show a higher correlation with each other compared with the term "Soil".

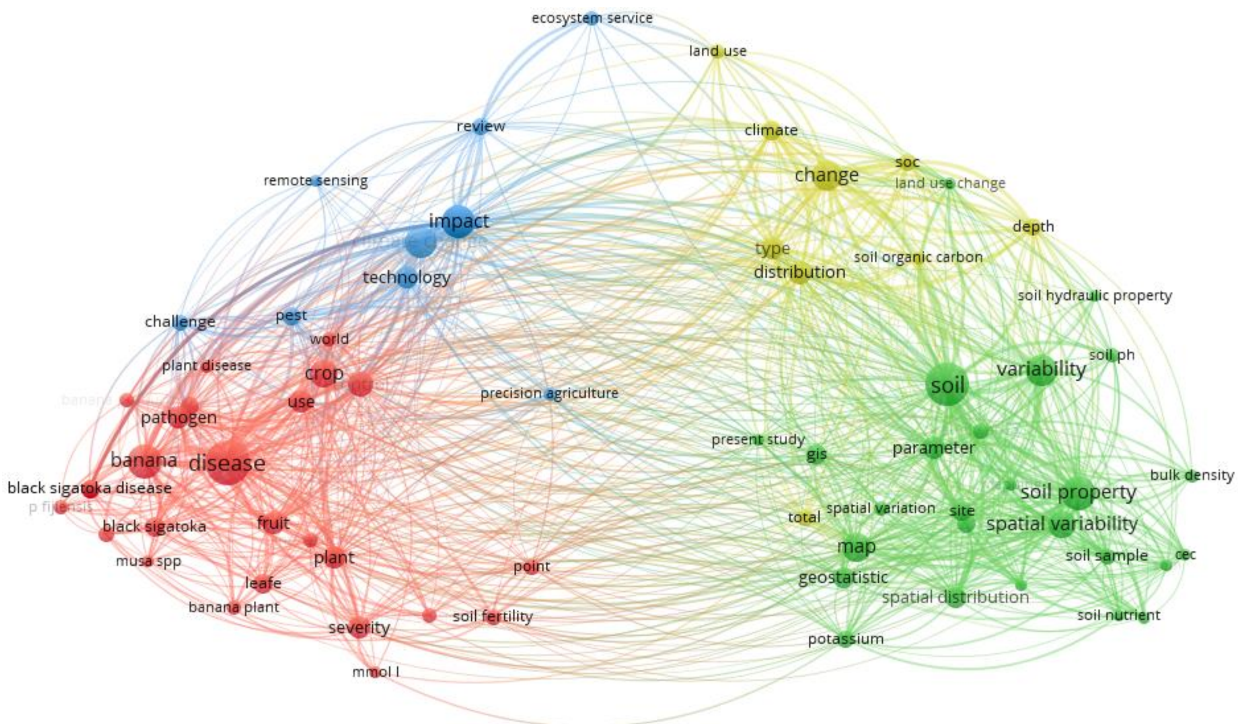

Figure 7. Co-occurrence mapping of titles and abstracts. Source: own elaboration.

Table 4. Summary of the mapping of the top 10 title and abstract terms. Source: own elaboration.

Keyword	Occurrences	Percentage	Links	Avg. pub. year
Disease	138	17.3	50	2017
Soil	129	16.2	63	2015
Banana	82	10.3	46	2016
Soil property	79	9.9	48	2017
Climate change	70	8.8	49	2017
Variability	66	8.3	53	2015
Change	62	7.8	53	2016
Impact	61	7.7	60	2017
Map	55	6.9	57	2015
Spatial variability	54	6.8	48	2015

3.2 Strategies to cope with climate change

Climate change poses a risk to food security by affecting crop physiology and productivity both directly and indirectly through interactions with pests and diseases. Although the relationships between host plants, pathogens, and environmental factors can be complex, recent studies are uncovering general trends on how plant pests and diseases might further impact crop yields in a changing climate [52]. Major contributors to production losses include agricultural pests and diseases, which together account for nearly 5 % of global GDP, equivalent to approximately US$ 1.4 trillion [28].

Currently, climate change is increasingly threatening sustainability in several major banana growing regions, requiring responses to effective management of black sigatoka (*P. fijiensis*), which has severe direct impacts on production as well as indirect implications through damage to human and environmental health caused by fungicides used for its control

[53]. Therefore, research is needed to address the monitoring of environmental conditions and management of black Sigatoka to increase crop yields, reduce costs, and investigate the effect of fungicides on the environment and human health.

Edaphoclimatic conditions affect banana crop yields in Colombia [24], [36], [54]. Edaphoclimatic conditions are influenced by dry and rainy seasons, affecting banana crop yield and facilitating black Sigatoka infection in cultivars [12]. Therefore, it is essential to study them for information that is widely used for the tropics and subtropics, providing a greater understanding of edaphoclimatic conditions associated with black Sigatoka infection and options for transferring knowledge and geospatial technologies between sites.

In terms of production and academic contributions, quantifying optimal edaphoclimatic conditions for banana productivity is critical to assess seasonal crop climate variability and black Sigatoka incidence and, subsequently, predict the potential impacts of climate change on banana production systems to ensure food security [8]. Ideally, this requires collecting data from experiments and field trials conducted under various edaphoclimatic and sanitary conditions to demonstrate their influence on crop yield.

In the last decade, the use of geostatistical methods in agriculture has increased the potential for developing comprehensive spatial frameworks that facilitate the establishment of agricultural databases and enhance both farm management and food security [44], [55]. These data systems enable farmers to retrieve spatially referenced agricultural information instantly, offering accurate location data that supports decision-making and improves the tracking of crop yields and the spread of pests and diseases [40], [56]–[59].

While the use of technologies in agriculture can help optimize crops and facilitate farm management decisions to solve food insecurity challenges, adopting geospatial technology requires large amounts of high-resolution spatial data and considerable time [44]. Therefore, it is crucial to have geospatial information to collect, store, integrate, query, display, and analyze geospatial data of soil and climatic conditions in banana crops at a temporal scale.

3.3 Global expansion of the Black Sigatoka

Black Sigatoka is a significant foliar disease for banana cultivation; it was detected in 1963 in southeastern Viti Levu, 60 km from the Sigatoka valley on the island of Fiji, where the disease reached epidemic proportions [20], [53] and has since spread throughout the tropics and subtropics, perhaps encouraged by climate change [15]. However, herbarium specimens indicate that it was present in Taiwan in 1927 [21] and in Hawaii in 1961 [12]. Dispersal in Latin America began in Honduras in 1972 and then moved to Africa in Zambia in 1973 [10], probably with infected plants from Asia imported for a banana breeding program [60]. By 1980, black sigatoka had spread more widely throughout Asia and Africa; by 1999, it had spread to the South American continent and the Caribbean [12]. In Colombia, it was first detected in Urabá in 1981, and six years later, it became endemic, where more than 600.000 infected banana boxes were reported, becoming the primary cause of production losses [54].

3.4 Climate and the Black Sigatoka

Due to climate variability, the Black Sigatoka has become more aggressive [61]. In particular, [49] show that agricultural trade and climatic conditions can play essential roles in the spread of black Sigatoka between countries. Even with stringent import restrictions and safety measures in place to theoretically prevent the spread of crop diseases between countries through the transfer of diseased material, the diseases can still be transmitted over long distances from other locations under favorable climatic conditions.

Many studies report that climatic factors influence black Sigatoka infection (Table 5) and relate disease incidence and severity to rainfall [9], [12], [54], [62]. However, other authors have reported that other climatic variables, such as relative humidity, evapotranspiration, solar radiation, and leaf wetness, affect disease severity [12], [18], [49], [63], [64].

Table 5. Climatic variables associated with black sigatoka infection. Source: own elaboration.

Climatic variables	Objective of the study	Authors
Precipitation, relative humidity, canopy temperature, canopy humidity, evapotranspiration and wind velocity	This research creates an empirical model to analyze the spread of black sigatoka between countries and its effects within individual nations, utilizing historical spread timelines, biophysical models, local climate data, and agricultural data at the country level.	[49]
Precipitation	This study determined the relationship between climate, edaphic properties, and the incidence of black sigatoka.	[54]
Precipitation and temperature	This study evaluates the influence of different climatic patterns represented by rainy and dry seasons on the effectiveness of biological and chemical control methods to mitigate Black Sigatoka disease in banana plantations, in order to identify more effective management strategies under different climatic conditions.	[9]
Precipitation and temperature	This study evaluates the relationship between black sigatoka severity in different geographical areas and factors such as plant age, rainfall, and temperature, in order to better understand the patterns of disease incidence under different climatic conditions and growth stages of banana plants.	[62]
Temperature, relative humidity, and precipitation	This study uses the CLIMEX model to globally map the distribution of black sigatoka, considering climatic variables and the role of irrigation to validate the model as an index of disease pressure.	[12]
Precipitation, relative humidity, temperature, and solar radiation	This study developed a predictive model of black sigatoka disease severity in banana crops, integrating climatic variables in order to improve the scheduling and efficacy of fungicide application for disease control.	[63]
Temperature, precipitation, solar radiation, relative humidity, and wind velocity	This study designs a wireless sensor network based on predictive models to monitor climatic variables associated with Black Sigatoka in banana crops to facilitate early scheduling of fungicide treatments.	[64]
Temperature, relative humidity, precipitation	This study determines the relationship between black Sigatoka severity and climatic conditions by correlation analysis with the quantification of M. fijiensis spores in different sampling periods (dry and rainy seasons).	[18]

3.5 Soil and Black Sigatoka

Sustainable soil management for banana crops depends on the availability of nutrients in the soil. It is conditioned by a nutrient balance in which the concentration, fixation, and losses in the production system are evaluated [65]. Plants growing in excellent and fertile edaphic conditions usually show a lower incidence and severity of pests and diseases than those growing in poorer soils [66]. Organic matter, nutrients, and soil physicochemical conditions have been reported to reduce disease severity and improve banana crop yields [66]-[68].

Some research has shown relationships between soil fertility and black Sigatoka severity [16], [24], [36], [48], [54], [69]–[71] (Table 6), indicating that the higher the soil fertility level, the lower the severity of black Sigatoka. Fertile soils, particularly those rich in organic matter, encourage increased root branching. This leads to improved absorption of water and nutrients, resulting in more vigorous plants with more effective leaves. These plants quickly produce new foliage, which helps them endure less damage, experience slower progression of symptoms, have less leaf area affected, and enjoy a longer lifespan for their leaves [66]. Thus, appropriate and balanced fertilization can help minimize nutritional imbalances in banana plants and decrease the frequency of fungicide applications needed to manage the disease [48].

Table 6. Soil variables associated with black sigatoka infection. Source: own elaboration.

Edaphic Variables	Objective of the study	Authors
Mg^{2+}, microporosity, clay content	This study determined the relationship between climate, edaphic properties, and the incidence of black sigatoka.	[54]
pH, Mg^{2+}, CIC, Cu, bulk density, clay content and microporosity	The association between soil physical and chemical parameters and the average percentage of infection (PPI) produced by black sigatoka was studied.	[24]
Soil moisture	This study uses the CLIMEX model to globally map the distribution of black sigatoka, considering the role of irrigation to validate the model as an index of disease pressure.	[12]
pH, organic carbon, total nitrogen, Ca^{2+}, Mg^{2+}, K^+	This study determines the severity of black sigatoka in relation to soil fertility in two different geomorphological zones.	[69]
Sulfur	This study characterizes the spatial variability of black sigatoka to examine its relationship with soil fertility in the Grande Naine variety.	[16]

3.6 Soil seen by spatiotemporal variability

Assessing spatiotemporal variability and analyzing the distribution of soil properties are important prerequisites for resource and crop management in agricultural areas [72]–[75]. However, little is known about the spatio-temporal distribution and variability of soil properties at the local scale [73], [76]. Characterizing the heterogeneity of the distribution of soil properties is difficult because sufficient samples are required to characterize sites. Consequently, information on soil spatial variability is available from very few sites worldwide. It is usually limited to a single set of soil physicochemical characteristics [77], which has changed thanks to technological developments.

Studies on the effect of soil management have shown that crops increase the potential for soil erosion due to the decomposition of aggregates, reduction of cohesion, and consequently, decreased nutrient content [73], [78], [79]–[86]. Soil properties also vary considerably depending on crop type and tillage intensity [73], especially in banana crops [16], [45], [68], [87], [88]. Therefore, characterizing the spatial variability and distribution of soil properties is essential for predicting the rates of agricultural processes related to climate variability and anthropogenic climate change [89], [90]. Mapping spatiotemporal variability allows for dynamic monitoring of soil properties and locating homogeneous sites that require careful management for crop development [73], [91].

Temporal variability of soil properties has been studied by several authors who have reported significant differences in property values [73], [92]–[97]. Some researchers included within their investigations temporal variability by measuring soil parameters at different crop ages [94], [98], and others evaluated the effect of climatic variability on temporal changes in soil properties, evidencing that this variability affects moisture conditions, pH, salinity, organic carbon, micronutrients, and other properties [92], [99]–[101].

In research examining the spatial and temporal patterns of soil properties, both traditional statistical methods and geostatistical techniques have been extensively utilized [73], [79], [102]–[106]. Geostatistics uses autocorrelation and digital mapping methods to infer the spatial distribution of resource properties [107], [108]. Information provided in digital maps using geostatistical methods leads to better management decisions and a precision agriculture approach, aids problem-solving, and maintains soil productivity and sustainability [78], [109]. However, to the best of our knowledge and according to what has been reviewed, the implications of spatial and temporal variation of soil properties associated with crop management and climate variability have been little studied in the banana-growing area of Colombia.

3.6.1 Spatial variability of soils

Spatial variability of edaphic properties is influenced by land use type, topography, formation characteristics, depth, human activities, and time [75]. Assessing spatial variability through sampling is an essential step in precision agriculture processes that helps farmers make informed decisions regarding the distribution of agricultural inputs [110]. Spatial analysis of soil properties can be performed using various statistical methods, geostatistical methods, and geographic information system (GIS) approaches that facilitate interpolation of geographically located data to improve interpretation accuracy and digital mapping of the resource [111].

The analysis of spatial variability in soil utilization employs pattern-based statistics, a type of geographic analysis also known as location analysis [111]. This approach utilizes geostatistical and geometrical techniques to understand spatial patterns [111]. It involves applying statistical and data manipulation techniques to information that can be stored in a local geodatabase [111]–[113]. Spatial soil analysis reveals characteristics of the sample location, such as whether the samples are scattered or clustered. The spatial information itself pertains to the position, area, shape, and size of the defined area, and this data is typically stored as coordinates and topology [111], [113], [114]. One key outcome of this spatial analysis of soil properties is the creation of digital maps.

Digital mapping aims to identify and define soil units with some level of uniformity, delineated by clear boundaries. Nonetheless, soil characteristics are seldom entirely consistent; even within the same mapped units, there can be considerable random fluctuations in properties, complicating the detection of changes in average values between different mapping units [115], [116].

According to [115], [117], properties change continuously due to the impacts of climate variability and the effects of different soil management practices. Soil spatial variation can present in different patterns. For example, it might show relatively stable changes within certain map units but encounter sharp shifts in average values at soil boundaries. Alternatively, soil property variations might be smooth and continuous, with minimal and consistent fluctuations. Another possibility is having slight, non-random changes within soil units, along with either smooth or abrupt transitions in average values at boundaries. Lastly, soil properties might display sudden changes in variance at boundaries, whether or not there are changes in the average value [115].

3.6.2 Temporal soil variability

The properties of soil are not static; they change over time [92]–[101], [118]. This variability stems from both intrinsic processes, which are linked to natural phenomena, and extrinsic processes, which are related to human management and cultivation practices [119]. Geological, hydrological, and biological factors are the primary intrinsic sources that influence soil formation and lead to variability. In contrast, extrinsic variability often results from differences in cultivation techniques and management, including variations in tillage methods, irrigation and drainage practices, and the management of crops and crop residues [119]. The temporal variability of soil can be analyzed in relation to plant age and through annual, seasonal, or daily cycles [115].

Temporal variability in soil can manifest during the growing season, and it can also occur from year to year, month to month, or even day to day, often influenced by weather and climate conditions. The physical properties of soil, such as moisture content, bulk density, aggregate stability, and penetration resistance, are interconnected and significantly affected by both climatic variability and climate change [119]. Similarly, chemical properties like pH, salinity, and soil organic carbon content are also impacted by these climatic factors [92], [99] –[101].

3.7 Application of geostatistical techniques and GIS for pest and disease detection

GIS technology utilizes a combination of information management tools and methods that have enabled the administration, editing, and analysis of geospatial data on a global, regional, and local scale [120]. In the agricultural context, remote sensing technology uses data from crops and images taken from satellites, aerial remote sensors, and ground equipment [57], [121]. The processed data can be deconstructed into spatial layers that can then be processed and analyzed in a GIS in multiple ways to reveal crop conditions and monitor pests and diseases [44].

Several studies have applied GIS approaches for the detection of Black Sigatoka in banana crops, using images taken by hyperspectral sensors to characterize the severity of the disease [17], [28], [50], [122]–[124]. These studies have demonstrated that the implementation of hyperspectral sensors is an effective tool for early disease identification, capturing detailed data on leaf reflectance, which allows for the detection of subtle differences in crop health that are not visible to the human eye. Previous research has leveraged these capabilities by correlating the data with disease severity indicators, thus improving decision-making in the management of Black Sigatoka [16], [45], [87], [125].

These studies show that geostatistical methods have been fundamental in describing the spatial and temporal spread of Sigatoka in banana crops. For example, the use of kriging in specific studies [16], [68], [87], [88] allowed for modeling the distribution of the disease and generating predictive maps of the most affected areas. However, these studies demonstrate that the accuracy of these models depends on the density of the sampling points, the experimental setup, which includes the type of banana and the extent of the area to be studied. These factors ensure the effectiveness of the geostatistical tools. Table 7 presents the cited studies, detailing the geostatistical methods and the experimental setup used to evaluate Sigatoka infection in banana crops.

Table 7. Geostatistical methods applied to experimental sampling design and visualization to analyze sigatoka infection in banana crops. Source: own elaboration.

Banana type	Experimental area	Sampling points	Avg. distance between points	Statistical and geostatistical analysis	Type of software used	Ref.
Prata-Anã	1.2 ha	27	18m x 18m	Pearson correlations Variogram analysis Maximum likelihood estimation method Pip effect Kriging interpolation	PROC CORR in SAS R package using geoR package	[68]
Cavendish cv. Gran Enano	30 ha	71	100m x 100m 50m x 50m	Kruskal-Wallis test Shapiro-Wilk normality test Brown-Forsythe robustness test Modified Levene Normality assumption using the Skewness asymmetry coefficient. Empirical semivariograms Kappa smoothing Pip effect Ordinary Kriging	R software using the kruskal function of the agricolae package, levene. test function of the lawstat package geoR package, variog.mc.env function, variofit function, krige.control and krige.conv functions.	[87]
Pacovan	2 ha	30	3m x 3m	Autocorrelation analysis Lloyd aggregation index Geostatistical interpolation maps Pearson correlation	LCOR2 Program morlloyd program (Microsoft Excel) Surfer program PROC IML program	[88]
Grand Nain	0.09 ha	30	30m x 30m	Determination of isotropic semivariograms Stationarity assumption of the intrinsic hypothesis Mean square error function Standard error of prediction and self-validation (jackniffe) Degree of spatial dependence Interpolation of the data by ordinary kriging Pearson correlation	GS+ v.7.0 Statistical Analysis System statistical software	[16]

Table 7 shows that the evolution of statistical and geostatistical methods has advanced over time, highlighting geostatistics as key in the spatial modeling of Sigatoka infection. The transition has moved from basic approaches of correlation and autocorrelation analysis to more complex techniques, such as semivariograms and kriging, which allow for an accurate representation of the disease's spread. Additionally, the use of software has shifted from GS+, LCOR2, Surfer, among others [16], [88], to R [68], [87], facilitating the integration of advanced packages to perform robust analyses, thereby improving inferences and predictions in the management of Sigatoka.

In this regard, geostatistical analysis has proven to be an important tool for understanding the distribution and severity of Sigatoka in banana crops, as the spatial characterization of the disease is essential for its management. However, [88] emphasized the need to consider climatic variability and soil conditions that influence the incidence and severity of the disease. This led to studies such as [16], which applied geostatistical techniques to analyze the relationship between soil fertility and Black Sigatoka severity, using spatial distribution maps to identify critical areas within plantations. Similarly, [68], through geostatistical techniques, evaluated the correlation between Sigatoka severity and soil properties, considering climatic variables. As a result, their study employed advanced spatial analyses to map the disease and relate it to soil nutritional factors, highlighting the need for data-driven agronomic approaches to improve disease management. Likewise, [87] employed spatial modeling to study Black Sigatoka in Cavendish banana cv. Gran Enano, revealing distribution patterns that can guide decision-making in precision agriculture.

Nevertheless, despite these advances, the integration of new technologies, such as hyperspectral drones, satellite sensors, and/or machine learning techniques, remains a challenge for new research. These tools, combined with geostatistical analysis, would allow farmers to adopt more precise and efficient strategies for Sigatoka control, such as more targeted fungicide applications and improved monitoring programs [9], [32], [33]. Previous studies [17], [28], [50], [124] have shown advances in machine learning techniques and hyperspectral imaging applied to disease management or detection in bananas. However, none of those reported so far have associated these techniques with soil properties data and climatic variables.

For example, [17] evaluated the use of hyperspectral images to detect the early stages of Sigatoka through a penalized logistic regression model (PLS-PLR), achieving 98 % accuracy. This advancement allows for disease identification before it becomes visible to the naked eye, although it still does not incorporate climatic or soil variables into its analysis. [50] also developed machine learning-based models, such as SVM and neural networks, for early Sigatoka detection, demonstrating the potential of artificial intelligence techniques in precision agriculture, though it still does not account for environmental factors. Similarly, [124] designed a hyperspectral imaging system to detect the disease presymptomatically, using advanced optical techniques, but without yet integrating geostatistical or soil data. Finally, [28] employed drones and machine learning algorithms to monitor Sigatoka, demonstrating that remote sensing combined with artificial intelligence can surpass traditional methodologies, although it did not consider the influence of climatic and soil variables on the spread of the disease.

3.8 Climate variability and detection of Black Sigatoka in Bananas

Climate variability poses challenges to water resources, diminishes crop yields, and raises the prevalence of pests and diseases, significantly affecting agriculture, particularly in tropical areas. With the imminent climate risks to agricultural output and food security, there is a growing emphasis on global and national programs and policies to prioritize adaptation strategies for agricultural production in response to climate change [126].

The FAO forecasts that food demand will double by 2050, posing a significant challenge for the scientific community to boost agricultural productivity [126]. Therefore, studying the influence of climate variability and the relationship between black Sigatoka and edaphoclimatic conditions requires an appropriate methodology. In response to the spatial dependence between crops and plant diseases, GIS, remote sensing, and spatial analysis techniques have been employed in epidemiological research in the last two decades. These techniques have enhanced the collection, storage, retrieval, analysis, and visualization of spatial data, leading to a deeper understanding of the factors that affect the emergence of epidemics [87], [125], [127]–[129]. This method produces more reliable results concerning the area's plant disease epidemiology and soil variability [125].

Spatial analysis through geostatistics has been commonly used to relate edaphic and climatic conditions to pest and disease severity [71]; some authors have studied its application in banana crops to describe Sigatoka behavior, obtaining patterns of disease behaviors explained by edaphic conditions [16], [45], [68], [87]. Other research on GIS and remote sensing approaches have oriented their studies on the detection of black Sigatoka associated with climatic conditions using simulation models of the disease using physiological responses to infection given optimal climatic conditions of temperature, precipitation, relative humidity, evapotranspiration, solar radiation, plant leaf wetness, among others [9], [12], [15], [18], [49], [52], [61]–[64], [125].

So far, research that has used and applied GIS approaches, remote sensing, and spatial analysis in banana crops to detect black Sigatoka has separately studied the edaphic and climatic conditions associated with the disease. Few investigations have studied the relationship between edaphoclimatic conditions and black Sigatoka, and those that have been conducted have not used GIS, remote sensing, or spatial analysis approaches for disease detection on a spatiotemporal scale [24], [36], [54], [65].

3.9 Geostatistics and soul sampling

Soil properties often display spatial autocorrelation, meaning that the values of these properties at nearby locations tend to be similar. Numerous studies have examined a wide range of soil properties, including morphological, physical, chemical, and biological properties, at the microscale level [16], [75], [78], [92]. However, our understanding of how these properties vary across both space and time at this detailed level remains limited. This understanding depends on the availability of field data, the application of geostatistical techniques, and the analysis of autocorrelation among these properties. Geostatistics, a branch of applied statistics, has emerged as a valuable tool for understanding and estimating spatial patterns in soil properties [115], [130]–[132].

In geostatistics, autocorrelation exists when there are relatively minor variations that are not entirely random in the value of a soil property [133]. In this sense, the distance between sampling points is a factor that influences the spatial variability of soil properties, i.e., the closer the sampling points are to each other, the more similar the values are, as opposed to values separated by more distant distances. Beyond the critical distance threshold, where autocorrelation is lost, soil property values no longer exhibit spatially correlated behavior and their relationships become random [134]. This type of spatial variation, occurring when the relationship between two sampling points cannot be accurately predicted based solely on their distance, can be quantitatively modeled using various techniques, with semivariogram models being the most common [115], [135].

The semivariogram is a technique used to study the spatial distribution of soil properties [136]; it helps model how the variance of soil properties changes as the separation distance between sampling points increases [115], [137]. In geostatistics, the semivariogram is essential for spatial prediction or kriging of a target geographic feature. It is derived by measuring the spatial correlation or covariance between sample pairs at various distances in a dataset to create empirical semivariograms. A graphical representation of the semivariable and the distance or lag corresponding to the separation of the pairs produces the semivariogram [115]. The procedure involves plotting the semivariable values against the separation distance and then applying functions–such as linear, spherical, or exponential models–to fit these data points [135].

3.10 The future challenge of climate change on the detection of Black Sigatoka in Bananas

By the end of this century, climate change is projected to have a significant impact on the agricultural sector in developing countries due to associated damages and high adaptation costs, with potential results in 1.30°C to 5.70°C increase in global average temperatures, depending on emission scenarios, whether low or very high [138]. Some critical challenges include increasing frequency and intensity of extreme weather events through higher temperatures and more variable precipitation, including heat waves, floods, and droughts, which can significantly affect the agricultural sector [139]. Developing countries account for ~70 % of the agricultural potential for climate change mitigation [140]. The agricultural sector is a significant contributor to global greenhouse gas (GHG) emissions, directly accounting for approximately 14 % of the total. Furthermore, agriculture indirectly increases emissions through land-use changes, particularly deforestation for agricultural expansion, which contributes an additional 17 % to overall GHG emissions [41], [139], [141]–[143].

In this context, banana crops play a key role in carbon sequestration through photosynthesis, contributing to mitigating climate change. However, the effectiveness of this sequestration can be affected by foliar diseases associated with the crop [144]–[146]. Studies have shown that CO_2 capture in banana crops reaches 80°t/ha at the production stage [144], with biomass contributions of the pseudostem ranging from 75 % to 78 % and leaves from 12°% to 17°% [5], [147]–[149].

Developing and implementing effective adaptation and mitigation strategies to minimize the impacts of climate change on crop foliar diseases is a major challenge [150]–[153]. Detection of foliar diseases has led researchers to work on image processing for classification and early detection of crop diseases; however, they face multiple challenges because the variability of shapes and colors in the images, together with climate change, pose an additional challenge in identifying multiple foliar diseases, especially when disease patterns are irregular [154]. State-of-the-art studies in the area indicate that challenges are related to noise in images caused by electronic devices and lighting effects, out-of-focus imaging, lack of in situ data containing images of infected leaves in crops, variability of climatic conditions, and selection of suitable electronic devices and images [155]–157]. With these disadvantages, some researchers have adopted drone cameras, but these also present limitations such as weather and flight time for imaging [28], [157]. Nevertheless, drone cameras are a convenient tool for small-scale disease monitoring and are useful for validating remote and proximate sensor data for crop health monitoring [158].

The detection of black Sigatoka in banana crops faces significant challenges under possible climate change scenarios. As the global climate undergoes alterations, the accurate identification of this disease in crops and the influences of environmental variables on its detection become more complex, forcing geographic information systems to constantly change the algorithms used. Increasing the intensity and frequency of extreme weather events, such as heavy rains or prolonged droughts, could favor the spread and severity of black Sigatoka, making timely detection even more critical. Thus, climate change poses additional challenges in detecting crop diseases, requiring ongoing research and adaptation strategies to ensure food security. Future research on the detection of black Sigatoka in banana crops should prioritize the development of climatically robust algorithms, autonomous detection using artificial intelligence methods, the establishment of real-time monitoring systems, the understanding of the genetic variability of the disease, the implementation of integrated management techniques, and all other measures that humans take to monitor the crop. These guidelines will help address the challenges of climate change, improve detection accuracy, and ensure disease and pest protection in banana crops.

4. CONCLUSIONS

In the specialized field that links precision agriculture, geospatial analysis, and climate change, the number and nature of key terms appropriately reflect the essential elements of this nexus. The results reveal international correlation through author keywords, titles, and abstracts of scientific documents. The study examines the evolution of research, identifying recurring concepts, methods, and phenomena related to black Sigatoka monitoring in banana crops. It highlights key approaches of precision agriculture in times of climate change, agricultural management tools, and components. These elements constitute a valuable source of information to guide researchers and academics in research projects in this field.

This review emphasizes the complex interaction between climate change and its elements, Black Sigatoka in banana crops, and soil properties. Future projections indicate that climate change will increase the severity of Black Sigatoka and substantially affect banana crop yields, particularly on farms that do not implement precision agriculture techniques. However, climate change mitigation and adaptation strategies can alleviate some of these effects, such as increasing carbon fixation and reserves and implementing precision agriculture on banana farms for soil and crop management. Furthermore, effective soil and crop management can help ensure food security. An integrated approach that combines efforts to address climate change and implement precision agriculture will be essential to reduce the severity of pests and diseases in banana crops.

The climatic and soil variables associated with Black Sigatoka infection in banana crops require agricultural management and handling strategies to reduce the incidence and severity of this disease, thus improving productivity and sustainability of banana crops. Climatic variables include precipitation, evapotranspiration, relative humidity, canopy humidity, canopy temperature, wind speed, solar radiation, temperature, and relative humidity, which directly influence the microclimate of banana crops, creating favorable conditions for the proliferation of the fungus *P. fijiensis*. Soil variables include Mg^{2+}, Ca^{2+}, K^{+}, pH, CIC, Cu, microporosity, clay content, bulk density, soil moisture, organic carbon, total nitrogen, and sulfur, which impact soil yield and reduce plant defense response, requiring the soil to have necessary nutrients to maintain an environment less favorable for disease development.

The use of geostatistical methods to measure Black Sigatoka infection in banana crops demonstrates the effectiveness of various statistical and geostatistical analyses in different experimental setups. These methods have been applied using various software and programs, some of which, like SAS and Microsoft Excel, are widely used in research, while others, like LCOR2 and morlloyd, are considered obsolete or less common today. On the other hand, programs like R with packages like geoR and agricolae, as well as Surfer and GS^{+}, represent modern and versatile options for spatial and geostatistical analysis in agricultural studies. This diversity in software use reflects the variety of approaches and tools available to researchers in the field of geostatistics applied to banana crops, requiring further studies for their application.

Geostatistical methods, such as kriging, are used to model the spatial and temporal distribution of Black Sigatoka, generating effective predictive maps when field data is utilized. These tools enable more precise interventions in affected areas, improving disease management. Additionally, precision agriculture, by correlating edaphic and climatic variables, mitigates the effects of climate change on banana crops, using technologies like hyperspectral drones and satellite sensors for more adaptive strategies, such as targeted fungicide applications. However, research must advance in emerging technologies such as machine learning and artificial intelligence (AI), which have the potential to enhance early detection and automate management processes. This should include data on edaphic properties and climatic variables associated with Black Sigatoka in banana crops.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors contributed substantially to the study's concept and design, the article's writing, and the critical revision of the manuscript for important intellectual content.

Luis Miguel Torres Ustate: Conceptualization, Methodology, Research, Visualization, Data curation, Formal analysis, Writing: original draft, and Writing: revising and editing.

Nelson Virgilio Piraneque: Conceptualization, formal analysis, Writing: proofreading and editing. Revision, proofreading and editing, Supervision.

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