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Huitzi, I., (2022, diciembre 11).

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# Mexico City Sinkhole Formation: Development of a Conceptual Model in a Non-Karst Environment

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# Geographic context

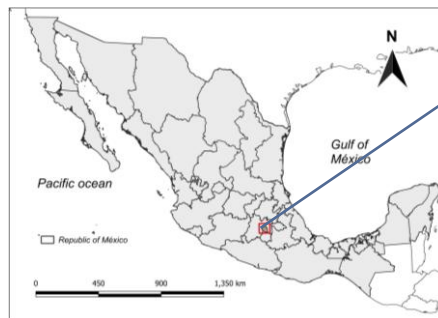
Mexico City is one of the most populated urban territories on the world, with more than 9 million residents (INEGI, 2020).

For its geographic location, the city is a hot zone to the presence of different natural hazards (García-Soriano et al., 2020; Novelo-Casanova et al., 2021).

Sinkholes formation stands out from the other phenomena for its strong presence in the city, where it has been recorded more than 500 events that have affected different routes of communication, homes and residents in the entire city since 2017 (SGIRPC, 2023).



Animal Político (2017).



Country of México



Lacustrine and pyroclastic deposits with lava intercalations.

Volcanic field with andesitic basaltic rocks, basalts, andesites and dacites.

Stratovolcanoes and domes, associated with epiclastic and pyroclastic deposits, of andesitic to dacite composition.

Volcaniclastic sequence and epiclastic deposits, interspersed with basaltic lava flows and andesite.

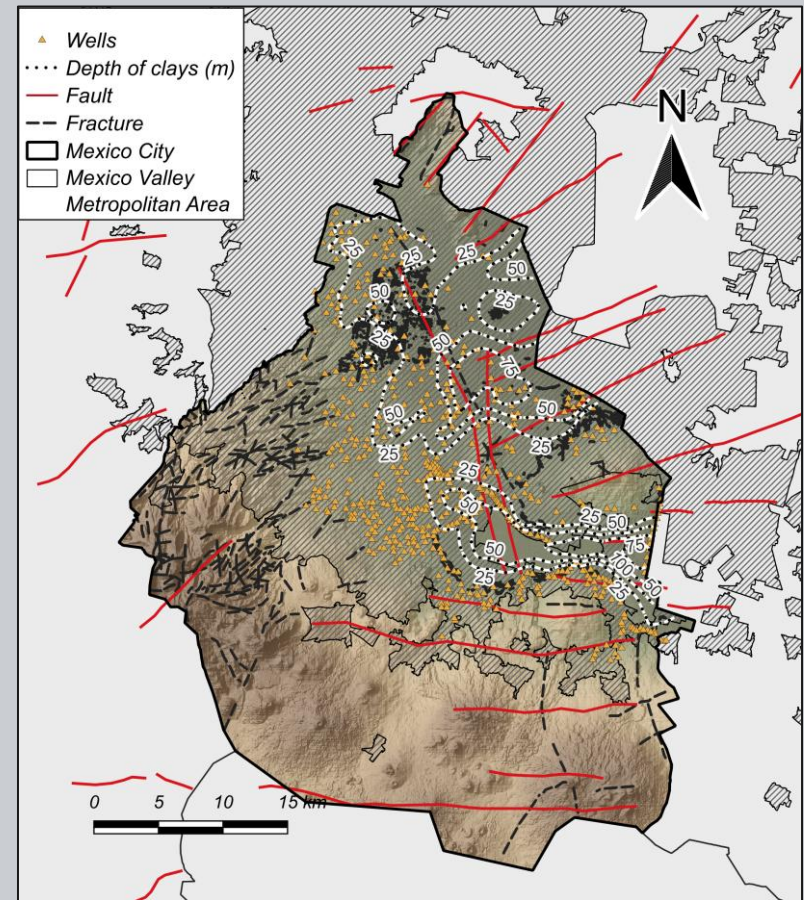


# Research questions

how do hydrogeological, geological factors and antropogenic activities interact in the formation of sinkholes in Mexico City?

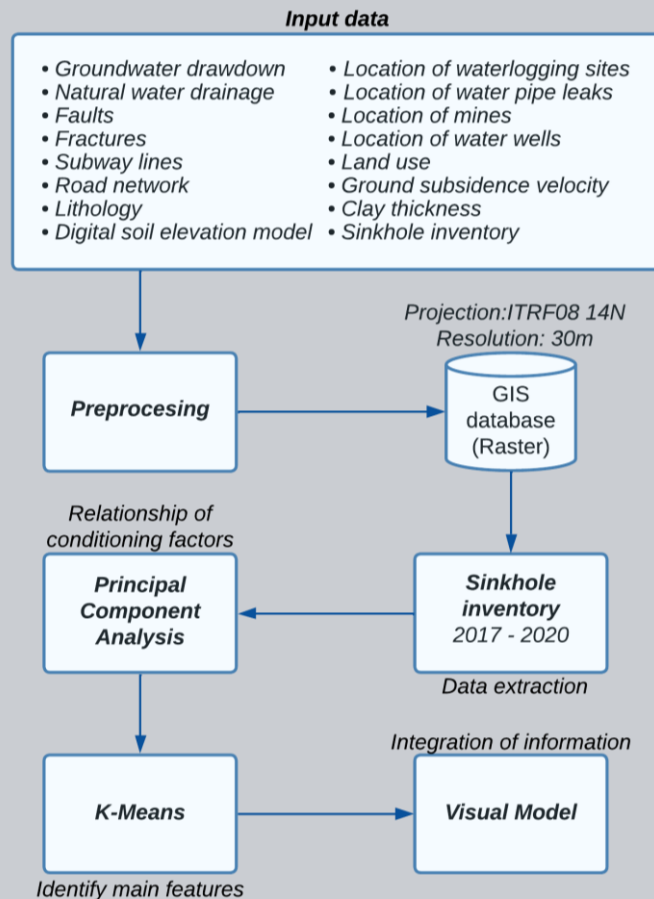
## Objective

The objective of this study is to develop a conceptual model that integrates and explains the formation of sinkholes in a non-karst environment, addressing the interplay of geological, hydrogeological, and antropogenic factors in Mexico City



# Methodology

1. Data preprocessing and storage in GIS database
2. Data extraction
3. Analysis of the relationship between conditioning factors
4. Identification of predominant factors
5. Information integration



## Principal component and K-Means cluster analysis

Principal Component Analysis (PCA) reduces the dimensionality of a dataset while retaining the maximum possible information.

Subsequently, the K-Means algorithm clusters the data into groups by minimizing the distance between each data point and its assigned cluster centroid (Forsyth, 2017).

The first 8 principal components from the PCA capture sufficient variance to enable the identification of meaningful patterns through the K-Means algorithm.

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Standard deviation	2.13	0.18	1.39	1.27	1.21	1.11	1.06	0.98
Variance portion	0.22	0.15	0.09	0.08	0.07	0.06	0.05	0.05
Cumulative variance	0.22	0.37	0.46	0.54	0.61	0.67	0.72	0.77

Figure 1. Principal component analysis. Most representative variables. PC1: Groundwater drawdown, elevation, natural drainage, waterlogging sites, mine, subway, clay thickness. PC2: waterleaks, water wells, fractures, faults, roadways, soil deformation.

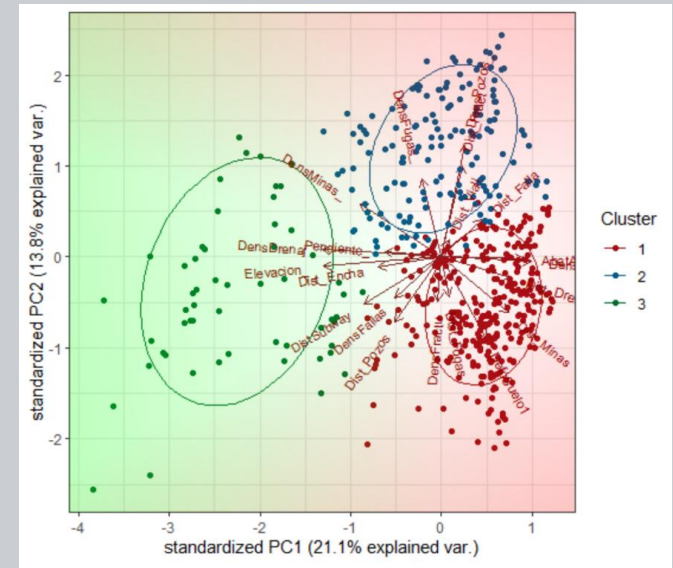
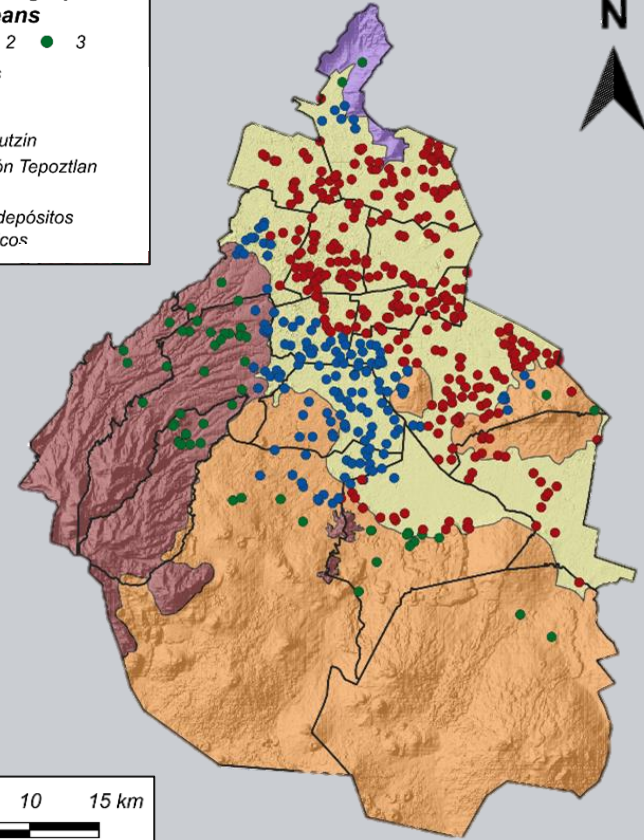
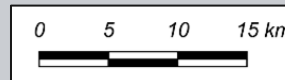
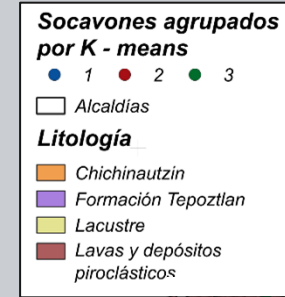
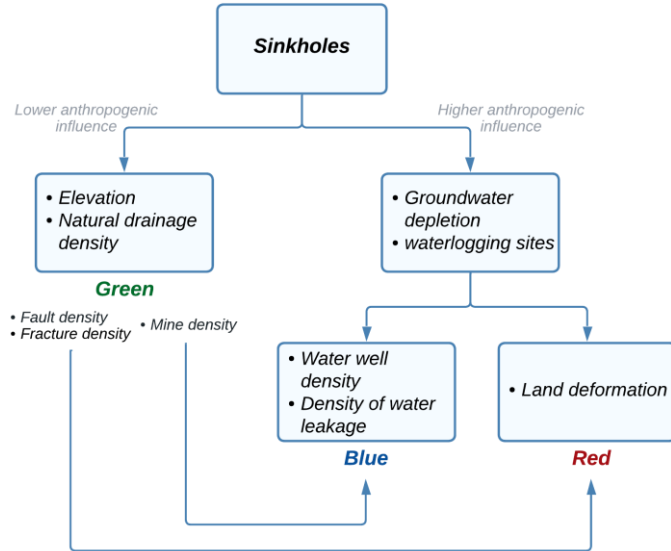


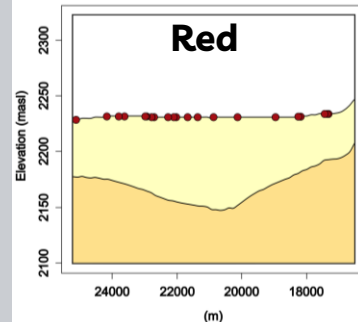
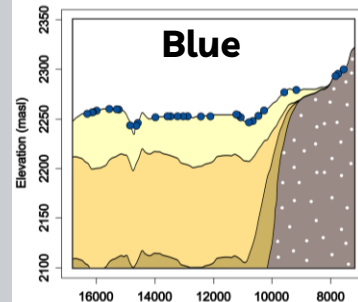
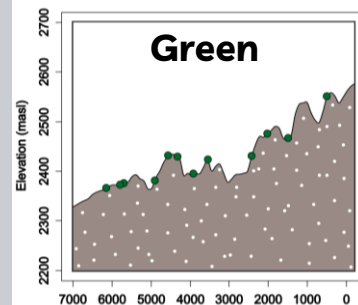
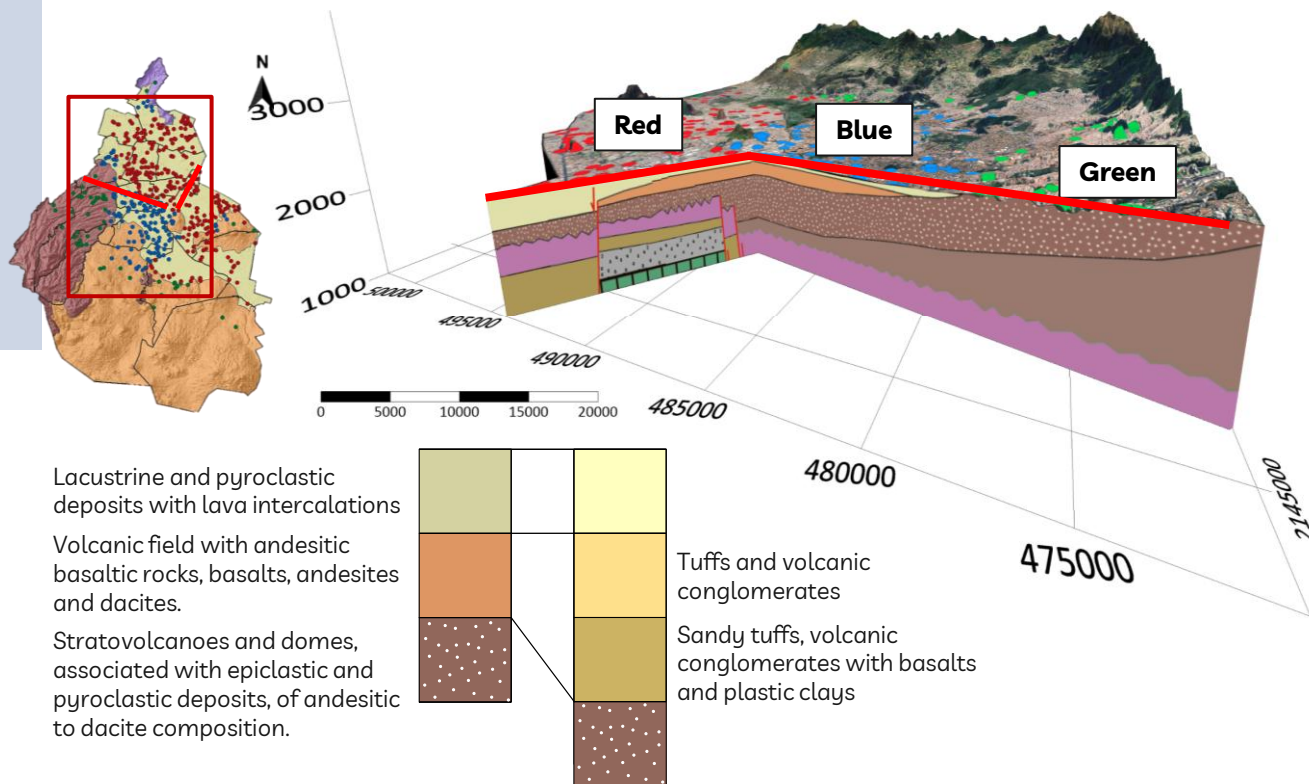
Figure 2. Results of k-means, 3 different groups were recognized (Green, blue and red).

# Conceptual model

The clusters identified through PCA and K-means algorithm exhibit variations in the predominant influence of conditioning factors.



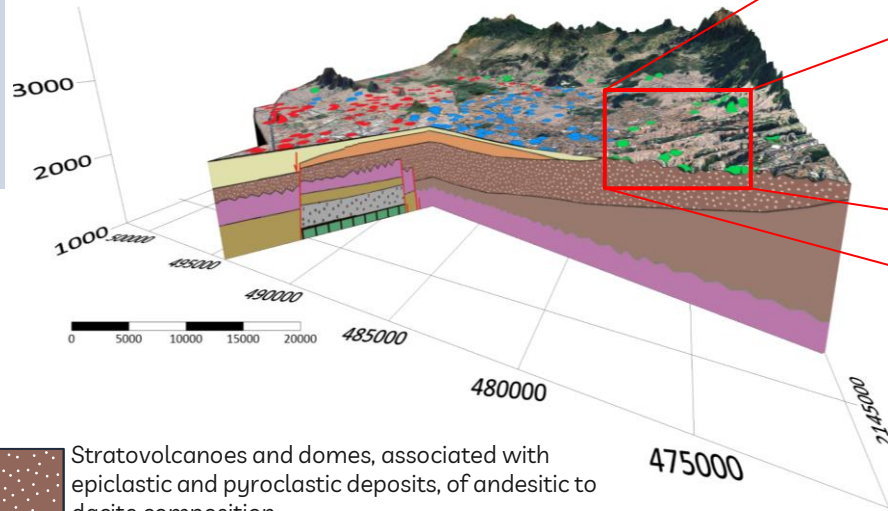
# Information integration



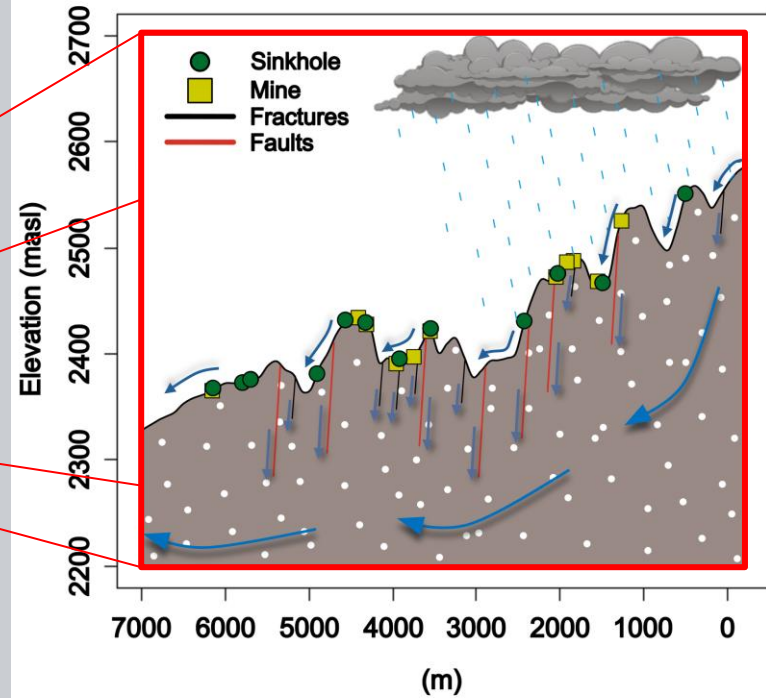


# Information integration

These sinkholes form when water flows quickly through weak zones (like faults or old mines) in volcanic deposits, causing erosion inside the ground.



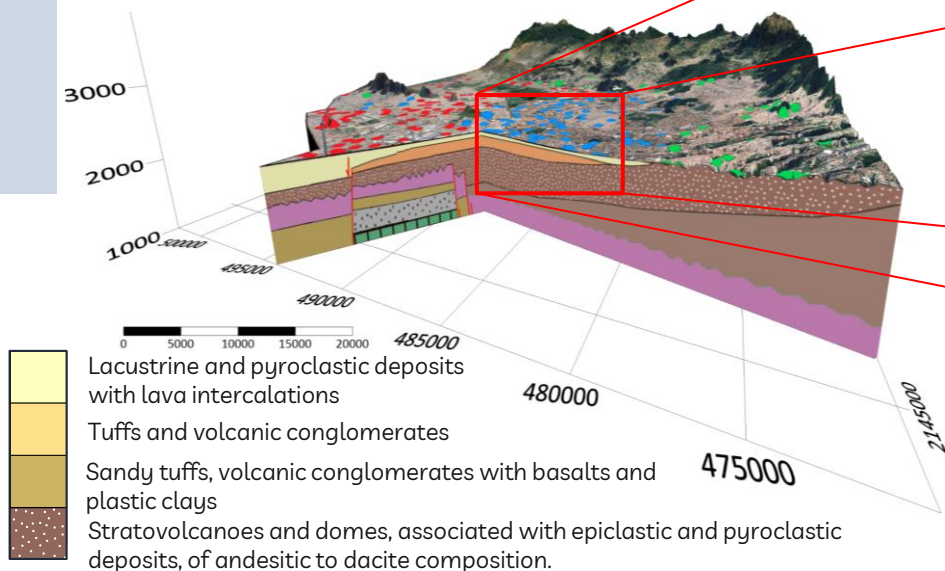
## Green



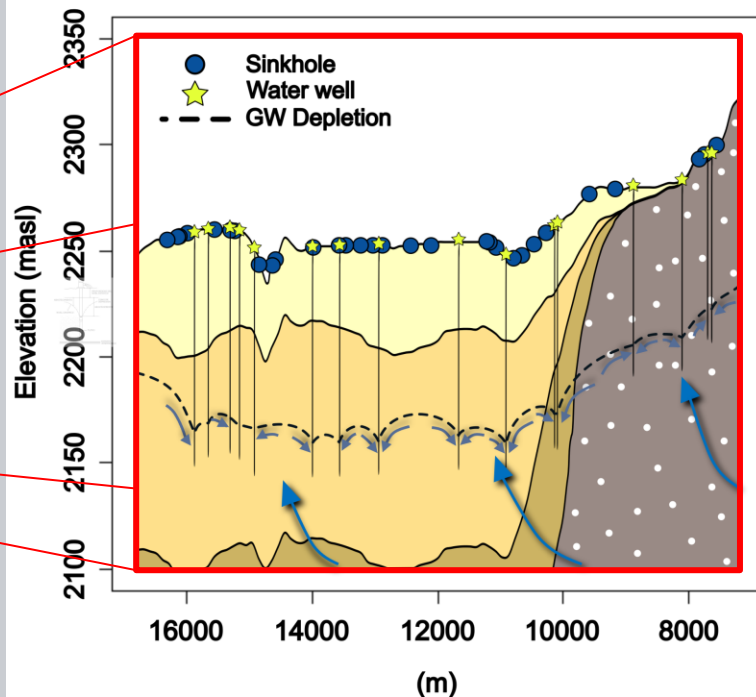


# Information integration

Esta zona se caracteriza por la sobreexplotación del agua subterránea, que reduce el nivel freático bajo los depósitos lacustres superficiales.

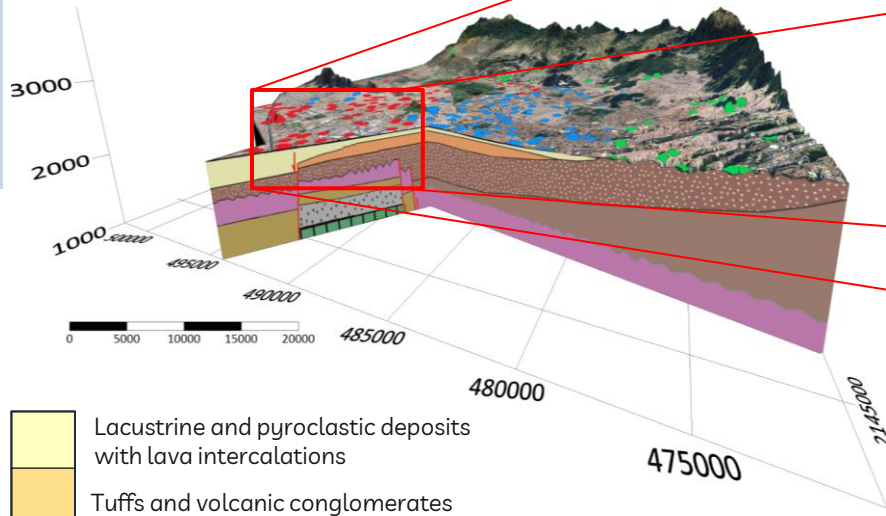


## Blue

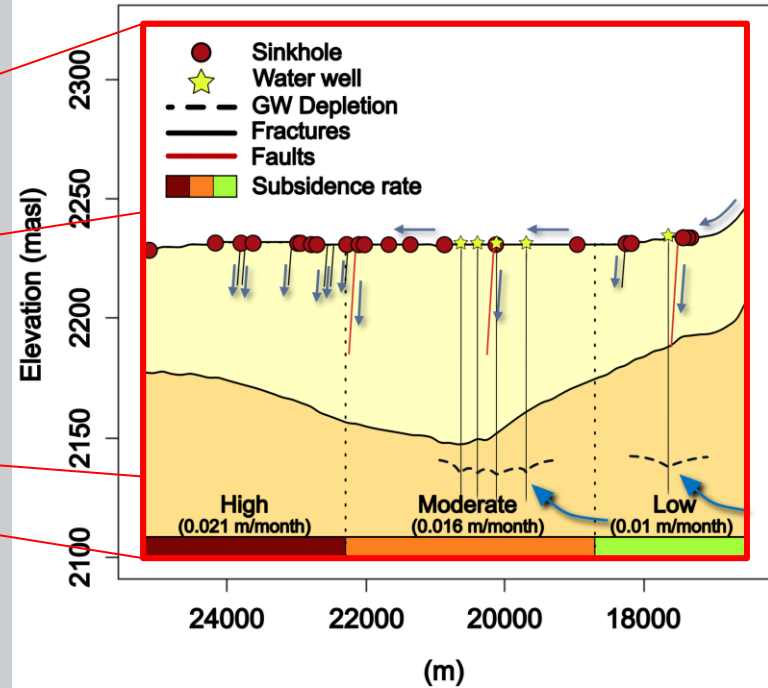


# Information integration

This zone is characterized by the land subsidence due to the compaction of lacustrine materials due to the overexploitation of groundwater, generating deformation and surface cracks.



## Red



# Conclusions

The use of statistical techniques such as Principal Component Analysis (PCA) and unsupervised classification algorithms like K-Means represents a powerful tool for analyzing and describing the behavior of complex phenomena, such as sinkhole formation.

The K-Means analysis classified sinkholes into three distinct types:

**Red** and **blue** clusters are mainly influenced by aquifer drawdown and well density. **Blue** sinkholes show a stronger relationship with infrastructure failures like water leaks, while red ones are more closely linked to subsidence and terrain deformation. **Green** sinkholes are associated with topographic features such as elevation and natural drainage.

This study highlights the multifactorial nature of sinkhole formation in Mexico City, demonstrating that distinct combinations of geological, hydrological, and anthropogenic variables influence their development.

These findings contribute to a more nuanced understanding of sinkhole dynamics in urban environments and offer a foundation for improving risk assessment and mitigation strategies in Mexico City.



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# Thank you for your attention!

Sergio A. García

If you have any questions, please feel free to email them to me at [garciacr93@gmail.com](mailto:garciacr93@gmail.com)

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## Mapping sinkhole susceptibility in Mexico City using the weight of evidence method



Geomatics, Natural Hazards and Risk



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### Assessing the relationship between contributing factors and sinkhole occurrence in Mexico City



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