[1] The manuscript "Preprocessing approaches in machine learning-based groundwater potential mapping: an application to the Koulikoro and Bamako regions, Mali " represents an important contribution aligned with the objective of theHESS journal and can interest the scientific community working on machine learning applied in water management. Concerning the scientific quality, I think that the used scientific approach and applied methods are interesting but the sections of the manuscript have unbalanced structure andsome sections are inappropriate and need in-depth analysis with improving the used English language. For that, I think this paper needs major modification and resubmission

Thank you for the positive feedback. We have strived to address all comments and suggestions, as well as to incorporate them to our manuscript.

General Comments. The introduction :

[2] -the section dedicated to the Reviews of literature concerning Groundwater potential mapping studies should be more developed with the presentation of the brief results of the pertinent studies.

Agreed. We have improved the second and third paragraphs of the introduction, with an emphasis on the machine learning literature. The review of literature concerning GPM studies now reads:

"Groundwater potential mapping (GPM) is recognized as a valuable tool to underpin planning and exploration of groundwater resources (Elbeih, 2015). GPM may be understood as a means to estimate groundwater storage in a given region, as a measure of the probability of finding groundwater, or as a prediction as to where the highest borehole yields may occur (Díaz-Alcaide and Martínez-Santos, 2019). However, it consists of computing spatially distributed estimates for a target variable (groundwater potential) based a set of dependent variables such as soil, lineaments, slope, geology, landforms, lithology, and drainage density. GPM often uses existing cartography, digital elevation models, aerial photographs, satellite imagery and geophysical information (Díaz-Alcaide and Martínez-Santos, 2019). Recent years have witnessed a growing interest in groundwater potential studies in Africa, largely as a result of the need to achieve the Sustainable Development Goal #6. The majority of these work with a combination of remote sensing, geographic information systems and geophysics (Delgado 2018, Adeyeye et al., 2019, Magaia et al 2018, Mpofu et al 2020, Owolabi et al 2020, Saadi et al 2021, Al-Djazouli et al. 2021), while others rely directly on the interpretation of information from borehole databases (Díaz-Alcaide et al 2017).

The literature shows that there are two main approaches to GPM, namely, expert-based decision systems and machine learning methods. Expert-based system methods have been used for a long time (DEP, 1993). These include multi-influence factor techniques (Magesh et al., 2012; Nasir et al., 2018; Martín-Loeches et al 2018), analytical hierarchy processes (Mohammadi-Behzad et al., 2019; Al-Djazouli et al., 2021), and Dempster-Shafer models (Mogaji and Lim 2018, Obeidavi et al 2021). Other frequently used methods are weight of evidence and frequency ratio analysis (Falah and Zeinivand, 2019; Boughariou et al., 2021). Machine learning is comparatively newer. A major difference between machine learning and expert approaches is that supervised classification uses the advantages of artificial intelligence to find complex associations among explanatory variables that might otherwise pass unnoticed. Hence, machine learning is well suited to map complex spatially-distributed variables such as groundwater occurrence. The GPM literature showcases a wide variety of supervised classification approaches. Thus, Al-Fugara et al. (2020) used mixed discriminant analysis to map spring potential in a watershed of Jordan; much like Odzemir (2011) mapped spring potential in a Turkish basin by means of a logistic regression method. Random forests have proved adept at mapping groundwater potential, both in mountain bedrock aquifer (Moghaddam et al., 2020), as well as in large metasedimentary basins (Martínez-Santos and Renard 2019). Other supervised classification methods include boosted regression trees (Naghibi et al., 2016), support vector machines (Naghibi et al., 2017b), neural networks (Lee et al., 2012; Panahi et al., 2020) and Ensemble methods (Naghibi et al., 2017a; Martínez-Santos and Renard, 2019; Nguyen et al., 2020b)."

[3] the introduction missed the presentation of the water resources problems in the study area and the need to elaborate the Groundwater potential map

Agreed. We have incorporated this information to the first paragraph of the introduction. This now reads:

"Water is crucial for human beings. Water provides food security, cleanliness and hydration, which translates into health, economic activity and arguably, better education opportunities (United Nations, 2002, 2010). Today, 2.5 billion people depend exclusively on groundwater for their domestic supply (Grönwall and Danert, 2020). Groundwater is particularly crucial in most of the Sahel, where rainfall and surface water are absent for several months (Llamas and Martínez-Santos, 2005; Díaz-Alcaide et al., 2017). In a context of climate change, in which rainfall is expected to decrease in most arid and semiarid regions and drought episodes are likely to become more intense (Arneth et al., 2019), groundwater resources will be increasingly relied upon. This is the case of the Republic of Mali, where access to drinking water and sanitation remains a concern for a large part of the population. In 2017, only 68% of the rural population had "at least basic" drinking water access, while 24% still relied on unimproved water sources (UNICEF/WHO, 2019). Since the country's aquifers are still relatively unknown, there is an impending need to endow water managers with tools to optimize groundwater use."

[4] Then the results discussed must be more in-depth, especially by explaining the results of the GPM obtained in connection with the hydrogeological context of the study area and theused explanatory parameters.

Agreed. We have rewritten the first paragraph of section 3.4 to comply with this observation. It now reads:

"Classifier outcomes were extrapolated to produce groundwater potential maps. Figure 10 shows the groundwater potential predictions rendered by each of the five best-performing algorithms (Decision Tree (DTC), Random Forest (RFC), AdaBoost Classifier (ABC), Gradient Boosting (GBC) and ExtraTrees (ETC)) under the two most effective scaling methods (MaxAbs scaling method and standardized scaling method). Red areas are those in which the algorithms have found a combination of explanatory variables leading to a negative potential. In turn, green zones represent a positive groundwater potential. GPM outcomes show a gradient characterized by the predominance of high potential areas in the south to a greater proportion of negative areas in the north. This appears to be related to rainfall patterns. Low potential areas occur around mountain outcrops of the southwest. The large green zone around the southern region corresponds to the weathering mantle of basement rocks. Groundwater in basement aquifers is most often found in weathered formations and piedmonts of the outcrops. Piedmonts may exhibit high GPM because these are essentially a mixture of weathered and transported materials (Martín-Loeches et al., 2018). This area presents smooth orography, so that high GPM is mainly determined by the weathered mantle. Previous research by Diaz-Alcaide et al. (2017) attributes a medium GPM for the southern part of the Koulikoro region. Discrepancies between this and our results likely stem from the fact that they used a regional approach. Furthermore, they relied on borehole yield data, while this work only classifies groundwater potential in positive-negative terms.

The central part of the agreement map shows a high potential for both methods, except in the higher altitude areas. This region, consisting of consolidated metasedimentary materials, has an average aquifer thickness of 30 to 50 meters (Traore et al., 2018). High yields are associated with the weathered mantle developed in the upper part instead than with the predominant lithology. This becomes evident in the metasedimentary outcrops located in the highlands. These present a low groundwater potential because fracturing facilitates rapid groundwater percolation into the plains, where it accumulates in the alteration zone. Areas near major rivers, such as the Niger, Sankarani and Bani, also have a high potential. This is attributed to the high permeability of alluvial sediments. The northern part of the study area, formed by consolidated and unconsolidated sedimentary materials, has a low groundwater potential. Although geological conditions are more favorable for groundwater due to the type of materials than in other areas of the region groundwater potential is limited by low rainfall. This is demonstrated by the feature importance analysis, which shows that precipitation is one of the two most important explanatory variables for groundwater occurrence."

[5] The methodology. (1) The hydrogeological context of the studies area is unfairly presented; (2) then the explanatory parameters used are unclearly presented. It is important to explainin-depth these used data to enrich the explanation of the results of GPM.

Agreed. We improved section 2.1 to provide a better hydrogeological background. It now reads:

"Figure 2 shows the major geological domains of the study area (BGS, 2021). The rocks that make up the Precambrian craton (south) are composed mainly of gneiss, schist and quartzite, representing metamorphosed volcanic-sedimentary sequences. The original sedimentary layers, which include shale, arkose, gravel and conglomerate, were intercalated with volcanic rocks, such as basalt, gabbro, dolerite, rhyolite and tuff. Further north, metasedimentary rocks of Proterozoic age, predominantly low-medium grade metamorphosed sandstones, with varying amounts of mudstone and limestone, take up over 50% of the study area. Volcanic outcrops (basalts and gabbros) are located in the central sector and in the northern end. Sedimentary rocks (sandstone, limestone and shale) of Cambrian-Carboniferous age and Cretaceous-Tertiary age occur in the northern third of the study area. Quaternary fluvial deposits associated with the Niger River are observed along the riverbed (Traore et al., 2018).

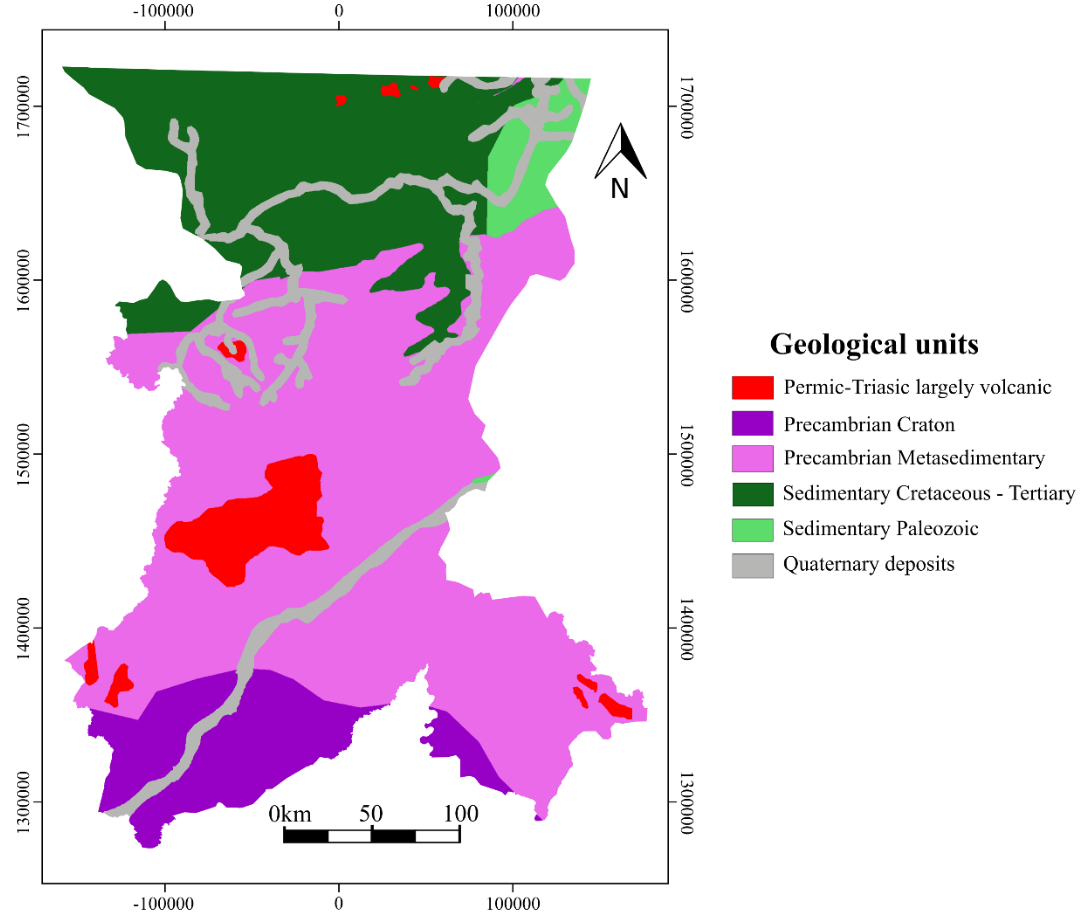

Figure 2*. Geological map with the main units that outcrops in the study area (adapted from BGS, 2021)*

From a hydrogeological perspective, four major aquifer units are distinguished (Traore et al., 2018). These include basement aquifers, aquifers linked to fractures and intergranular porosity of consolidated sedimentary rocks (Precambrian and Paleozoic), aquifers formed in intrusive volcanic rocks, and aquifers in unconsolidated sedimentary materials (Fig. 3).

Basement aquifers are mostly located towards the south of the Koulikoro region. These are characterized by a thick weathered mantle. The average thickness of the weathered formation over the basement in this region is between 10 and 50 meters. In these aquifers, groundwater flows preferentially in the weathered mantle, and, within this, the lower part is generally more transmissive due to lower clay content. The upper part is less permeable to flow but can still be important as a groundwater reservoir. Fractures can increase reservoir permeabilitym although their storage capacity is typically low (Martín-Loeches et al., 2018). Borehole yields range from 4 to 6 m^3/hour (Traore et al., 2018).

The Precambrian metasedimentary materials are located in the central part of the Koulikoro region. Metasediments are considered a mixed permeability aquifer: low permeability layers provide higher storage, while more fractured layers present higher permeability and lower storage. Mean aquifer thickness ranges from 30 to 50 meters and the average yield varies from 5 to 10 m^3*/hour. However, some boreholes yield exceeds 100 m3/hour. In the north, the fractured Paleozoic rocks allow water to flow through the sandstone and limestone layers. Average borehole yields are around 6 m*^{3}*/hour and the fractured horizons are about 40-45 m thick. Finally, unconsolidated sedimentary materials are composed by shales and argillaceous sandstone interbedded with limestone. The average borehole yields around 7 m*^{3}*/hour. The thickness of the saturated zone ranges from less than 100 m to over 400 m (Traore et al., 2018).”*

Furthermore, we now add a figure showcasing the region’s major hydrogeological domains (below).

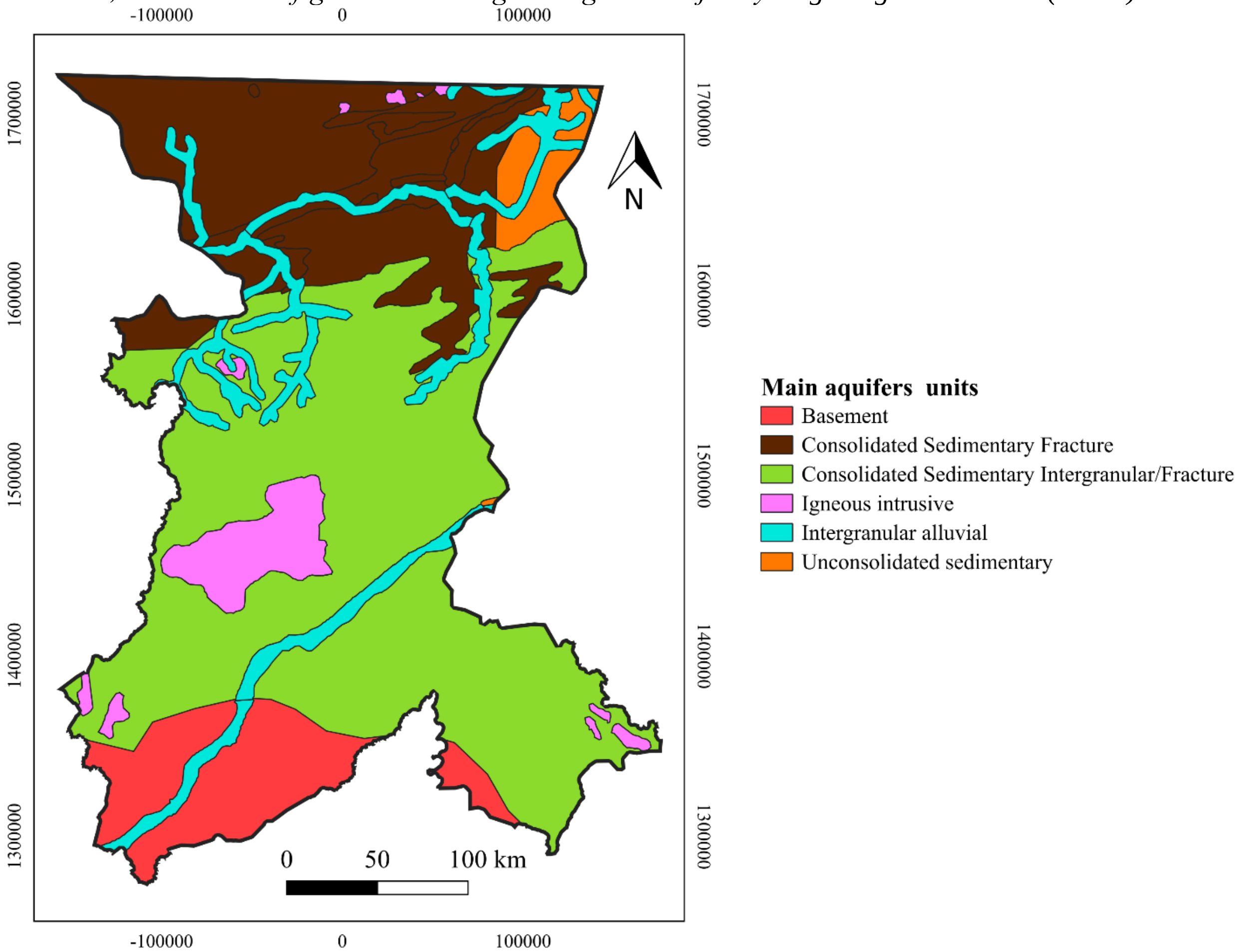

Figure 3. Main aquifer units of the study area (Adapted from Traore et al. (2018))

[6] (2) Then the explanatory parameters used are unclearly presented. It is important to explainin-depth these used data to enrich the explanation of the results of GPM.

Agreed. We have reorganized the explanatory variables section in two subsections. The first one deals specifically with the target variable, whereas the second is devoted to the explanatory variables. This now reads.

2.2.1 Target variable

For the purpose of this study, groundwater potential is defined as the likelihood of a drilled borehole being successful. Successful boreholes are those that yield sufficient water to justify the installation of a *hand pump (>0.5 m^3/h) (Foster et al., 2006). The target variable is therefore binary, and can be interpreted as the presence/absence of groundwater.*

For algorithm training, villages where more than 50% of wells were known to be successful were labelled "positive". The positive classification also applies to those villages with more than one high yield borehole (>10m^3/h). The others were labelled "negative". The resulting input dataset consisted of 650 villages, out of which 390 were labelled positive and 260 were negative. This comprises information from 3,345 boreholes, out of which 2,101 were successful and 1,244 were unsuccessful.

2.2.2 Explanatory variables

Groundwater recharge is influenced by five main factors (Kumar, 1997; Jyrkama et al., 2002). These are climate (e.g. precipitation, temperature, potential evapotranspiration), soils (e.g. texture, saturated hydraulic conductivity, moisture capacity), land cover (e.g. vegetation density and type), geomorphology (e.g. surface slope, drainage density) and hydrology (e.g. streamflow, water table depth).

Rainfall is the principal source of groundwater recharge. The amount of this recharge depends on the precipitation rate, as well as on the surface and subsurface factors that will allow or prevent infiltration. Soil is important because its characteristics (permeability, grain shape, grain size, and void ratio) control percolation. Higher infiltration potential is associated with sandy and gravelly soils, while clayey and silty soils rank among the least favorable for recharge (Díaz-Alcaide and Martínez-Santos, 2019). Integration of land use and land cover is often used in groundwater potential mapping studies because Land use changes, which are mostly induced by human activities, affect hydrological dynamics (Díaz-Alcaide and Martínez-Santos, 2019). For instance, croplands and forests, located in the southern part of the study area, could be associated with high groundwater potential because ploughing, root development and biological activity favor infiltration. Areas close to permanent water bodies also tend to correlate with a higher groundwater potential (Naghibi et al., 2017a). In contrast, urban settlements and wastelands are assumed to have low groundwater potential due to the presence of impervious surfaces, as well as to the absence of moisture (Magesh et al., 2012). Geomorphology may be useful in identifying features that may be favorable for groundwater infiltration and storage (Díaz-Alcaide and Martínez-Santos, 2019). Alluvial fans, sand dunes, weathering mantles, floodplains, and other accumulations of unconsolidated materials are generally recognized as the most interesting geomorphological features from a groundwater point of view (Venkateswaran and Ayyandurai, 2015). In contrast, landforms such as inselbergs, scarps, and ridges may be considered of little interest.

Hydrological factors such as drainage density or water table depth also play an important role in groundwater recharge. High drainage density means that runoff can be evacuated quickly and therefore infiltration is less probable. (Magesh et al. 2012; Fashae et al. 2014). In addition, a high drainage density can be assimilated to a higher erosion potential. Meijerink (2007) shows that parallels can be found between drainage density and soil permeability in certain geological settings. Water table depth is useful for mapping water tables to determine the main recharge and discharge zones of an aquifer.

Nineteen explanatory variables were selected based on an extensive review of the GPM literature (Díaz-Alcaide and Martínez-Santos 2019). Explanatory variables (Table 1) include lithology (Fig. 2), landforms, land use, soil, expected thickness (Fig. 5), rainfall, water table depth, vegetation-related indices (NDVI, NDWI), slope curvature, slope, topographic wetness index, stream power index, drainage density, distance from channels, clay content and clay mineral alteration ratio (Fig. 6). An additional layer with mean borehole flow rates per village was developed for the purpose of calibrating the results.

***Table 1**. Explanatory variables used in GPM. The scale/resolution, acquisition time and source of data for each factor are provided.*

Explanatory variables	***Scale/resolution***	***Time (dd/mm/yyyy)***	***Source of data***
Alteration Band Ratio	*30 meters*	*07-16/03/2020*	*Own elaboration from Landsat 8*
Clay content	*250 meters*	*N/A*	*SoilGrids250m 2.0*

Curvature	*30.53 meters*	*N/A*	*Own elaboration from DEM*
Saturated thickness	*30.53 meters*	*N/A*	*Own elaboration from DEM and borehole database*
Water table Depth	*30 meters*	*2010*	*Own elaboration from Borehole database*
Distance from channels	*30.53 meters*	*N/A*	*Own elaboration from DEM*
Geology	*1:5 million*	*N/A*	*British Geologycal Survey*
Geomorphology	*30.53 meters*	*N/A*	*Own elaboration from DEM*
Land use	*300 meters*	*2009*	*ESA Climate Change Initiative*
Soil	*1:3M*	*N/A*	*European Soil Data Centre*
Rainfall	*0.5°*	*1950-2009*	*CRU TS 3.21 dataset (Climatic Research Unit at the University of East Anglia)*
Drainaige density	*30.53 meters*	*N/A*	*Own elaboration from DEM*
Thickness matrix	*30.53 meters*	*N/A*	*Derived from DEM and borehole database*
Elevation (DEM)	*30.53 meters*	*23/09/2014*	*Shuttle Radar Topography Mission (SRTM)*
NDVI	*30 meters*	*07-16/03/2020*	*Own elaboration from Landsat 8*
NDWI	*30 meters*	*07-16/03/2020*	*Own elaboration from Landsat 8*
Slope	*30.53 meters*	*N/A*	*Own elaboration from DEM*
SPI	*30.53 meters*	*N/A*	*Own elaboration from DEM*
TWI	*30.53 meters*	*N/A*	*Own elaboration from DEM*

QGIS 3.0's Geomorphon plugin (Jasiewicz and Stepinski, 2013) was used to prepare the landform map. This approach uses DEM for the classification and mapping of landform features based on the principle of pattern recognition, rather than on differential geometry. By default the Geomorphon plugin classifies landforms in ten different categories. Because some of them can be expected to play a similar role in the context of GPM, these were subsequently regrouped in four (Fig. 5a).

Soil descriptions (Fig. 5b) of the study area were obtained from the European Soil Data Centre (Dewitte et al., 2013). About 45% of the region is characterized by the presence of Pisoplinthic Plinthosols a type of soils with plinthite (Fe-rich), strongly cemented to indurated concretions or nodules, humus-poor mixture of kaolinitic clay and other products of strong weathering (IUSS Working Group, 2015). It usually changes irreversibly to a layer with hard concretions or nodules or to a hardpan on exposure to repeated wetting and drying. Hypoluvic arenosols are present in 20% of the total surface and are characterized by being deep sandy soils, which explains their generally high permeability. These are residual sandy soils following in situ weathering of rocks generally rich in quartz. Nearly 13% of the study are characterized by Petric Plinthosols, that share multiple features with Pisoplinthic Plinthosols, which share multiple characteristics with Pisoplintic Plinthosols but unlike the latter are arranged in continuous or fractured sheets of connected concretions or nodules and are strongly cemented to indurated. Lithic Leptosols (very thin soils on continuous rock and extremely rich in coarse fragments with continuous rock from ≤ 10 cm from the soil surface), Haplic Lixisols (higher clay content in the subsoil than in the topsoil, as a result of pedogenetic processes), Eutric Regosols (very weakly developed mineral soils in unconsolidated materials) constitute about 15% of the study area.

The study area is clearly divided in terms of land use (Fig. 5c). There seems to be a clear association with the precipitation gradient. The southern part is characterized by open broadleaf deciduous forest (ESA, 2010). The central part is characterized by an alternation of shrublands, mosaics of cropland vegetation and rainfed cropland. West of Bamako, in the sparsely populated mountains, there are forests mixed with shrublands. The northern part of the study areais dominated by cropland mosaics and, further north, the landscape is made up of open grasslands, sparse vegetation and bare areas.

Boreholes in the study area are often drilled until the unaltered bedrock is reached. As a result, borehole depth can be a suitable proxy for aquifer thickness (Fig. 5d). Because the borehole database includes static level measurements, an expected saturated thickness layer was computed by subtracting one from *the other (Fig. 5d).*

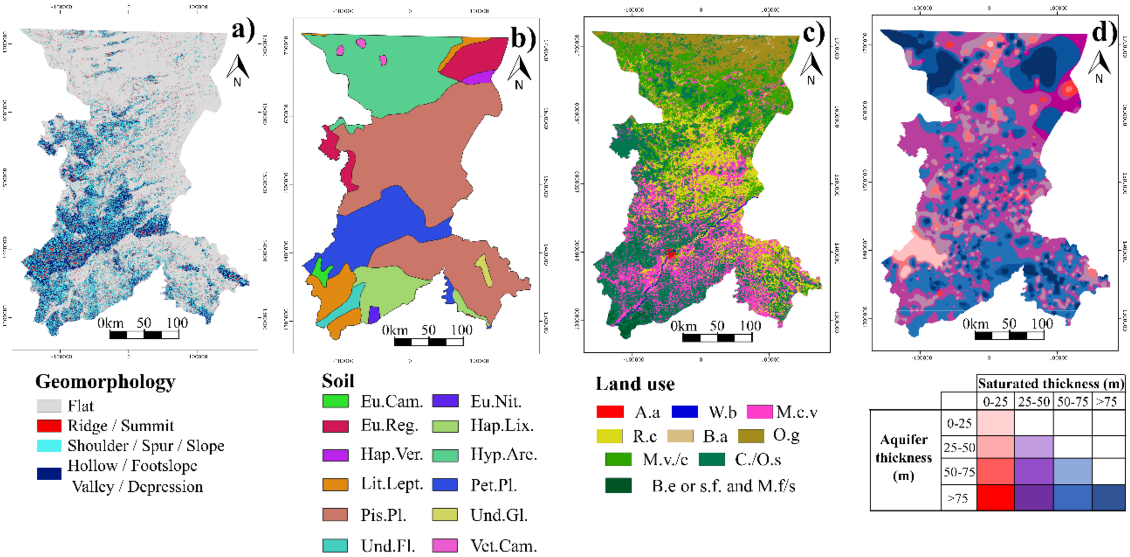

***Figure 5.** Explanatory variables used to predict the GPM: a) geomorphology b) Land use (A.a = artificial areas; W.b = water bodies; M.c.v = Mosaic cropland vegetation; R,c = Rainfed cropland; B.a = Bare areas; O.g = Open grassland; M.v./c = Mosaic vegetation/cropland; C./O.s = Close to open shrubland; B.e or s.f. and M.f/s = Broadleaved evergreen or semidecidous forest and Mosaic forest / shrubland) c) Soil (Eu.Cam. = Eutric Cambisols; Eu.Nit. = Eutric Nitrisols; Eu.Reg. = Eutric Regosols; Hap.Lix. = Haplic Lixisols; Hap.Ver. = Haplic Vertisols; Hyp.Are. = Hypoluvic Arenosols; Lit.Lept. = Lithic Leptosols; Pet.Pl. =Petric Plinthosols; Pis.Pl. = Pisoplinthic Plithosols; Und.Gl. = Undifferentiated Gleysols; Und.Fl. = Undifferentiated Fluvisols; Vet.Cam = Vetric Cambisols) d) expected thickness matrix.*

Another important variable in terms of aquifer recharge is precipitation, as both can be assumed to be correlated to some extent. Rainfall data in this case represents the mean annual precipitation for the 1950-2009 interval (Fig. 6a)

Satellite monitoring does not penetrate deep into the ground, but provides information about features that may be associated with shallow groundwater (Díaz-Alcaide and Martínez-Santos, 2019). This can be important in the case at hand, where the borehole database shows the static level to remain around 5-15 m below the surface (Fig. 6b). Vegetation-related indices can be useful in this context, particularly when computed at the end of the dry season (Fig. 6c,d). Take for instance the normalized difference vegetation index (NDVI, Fig. 6c), which is an estimate of vegetation vigour and is derived from the response of vegetation to red and visible infrared wavelengths (Xie et al., 2008). Similarly, the normalized difference water index (NDWI, Fig. 6d) is used as a measure of the amount of water in the vegetation or soil moisture (Xu, 2006). Based on Landsat 8 products, the NDVI and the NDWI are computed as per Eq. 1 and Eq. 2, respectively, where B3 represents the green band (0.53 - 0.59 μm), B4 is the red band (0.64 - 0.67 μm) and B5 is the near infrared band (0.85 - 0.88 μm).

$$NDVI\ (Landsat\ 8) = (B5 - B4) / (B5 + B4) \qquad (1)$$
$$NDWI\ (Landsat\ 8) = (B3 - B5) / (B3 + B5) \qquad (2)$$

The digital elevation model (DEM) was obtained from the radar-based Shuttle Radar Topography Mission (SRTM), with a resolution of 1 arcsecond (30 m). The topography is a relevant factor in groundwater distribution, storage, and flow, as well as surface runoff and infiltration, are partially constrained by surface features and parameterized by properties that can be extracted from the surface data (Elbeih, 2015). In this case, the DEM was used to develop the curvature (Fig. 6e), slope (Fig. 6f), topographic wetness index (TWI, Fig. 6g), stream power index (SPI, Fig. 6h) and geomorphology layers (Fig. 5a). It was also used to obtain the channel network, which is used in turn to elaborate a drainage density map (Fig. 6i). and distance from channels layer (Fig. 6j).

The Topographic Wetness Index (TWI) represents the ease with which water may accumulate at the surface (Beven and Kirkby, 1979). Similarly, the Stream Power Index provides a measure of the erosive power of flowing water (Moore et al., 1991).
The channels extracted from the DEM are used to develop the drainage density and distance from channels maps. Drainage density is computed as the total length of the streams per catchment unit area. Distance from channels was developed by extracting all major channels into a separate layer and developing 500, 1500 and 2500 meter buffers.*

Clay content in the first few meters of the surface largely determines the percolation of water into the aquifer. Therefore, an additional clay content layer (g/kg) in the top two meters of the terrain was considered (Poggio and de Sousa, 2020). This layer is obtained by state-of-the-art machine learning methods that use global soil profile information and covariate data to model the spatial distribution of soil properties around the world. (Fig. 6k). This layer provides information about subsurface clay content. To complement the information on clay content on the subsurface, an additional layer has been developed by combining bands 6 (short-wave infrared 1) and 7 (short-wave infrared 2) of Landsat 8 (Ourhzif et al., 2019). This layer provides information on clay content on the surface and the relationship with infiltration (Fig. 6l).

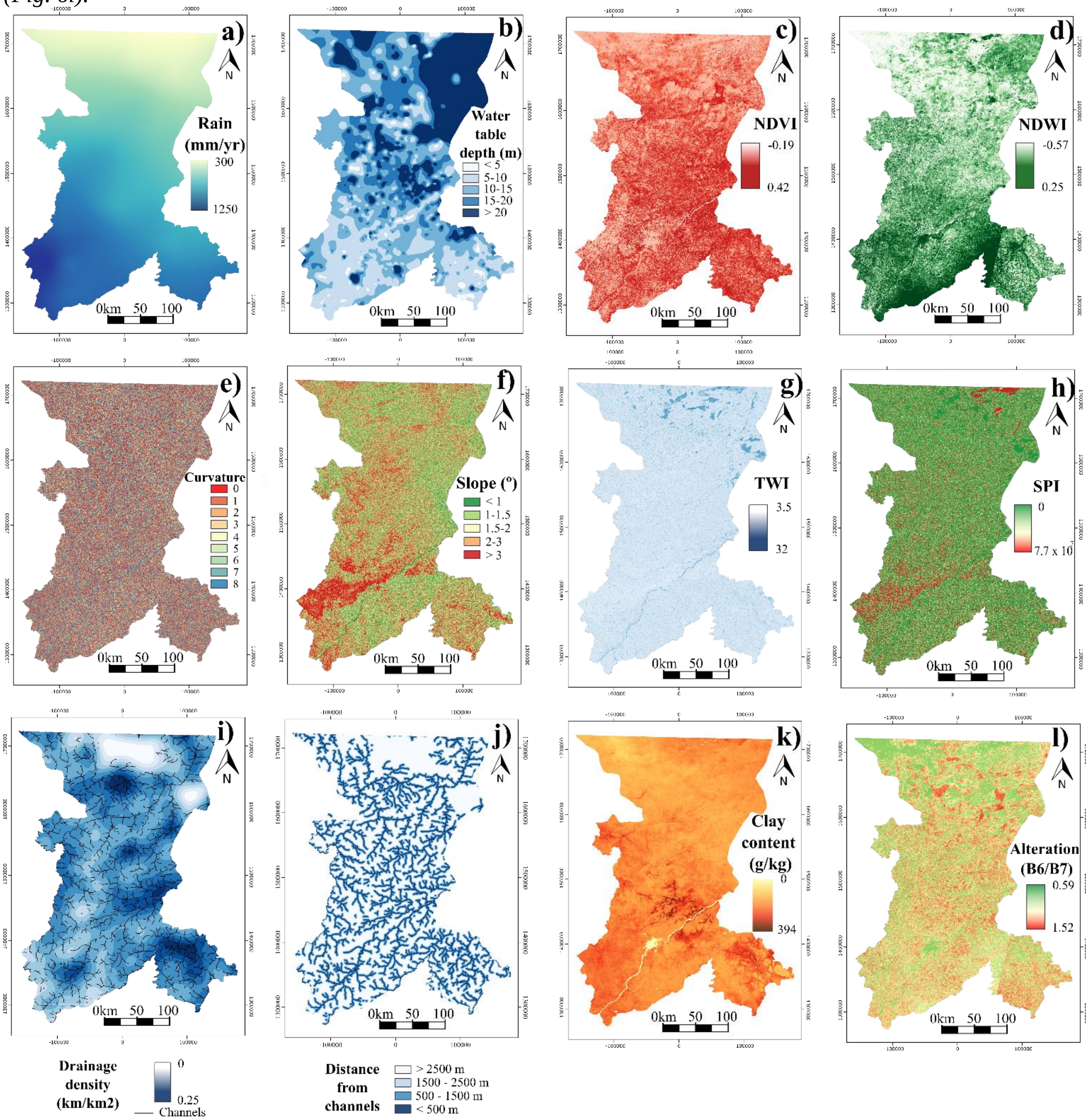

Figure 6. *Explanatory variables used to predict the GPM: a) rainfall (mm/year) b) water table depth (metersc) normalized difference vegetation index (NDVI) e) curvature f) slope (degree) g) topographic wetness index (TWI) h) stream power index (SPI) i) drainage density j) Distance from channels k) Clay content (g/kg) l) alteration band ratio (B6/B7)*

Revision suggestions:

ABSTRACT:

[7] line9: "Groundwater is crucial for domestic supplies in the Sahel"

it is necessary to precise the location. which Sahel?

In our view, the dependence on groundwater for rural groundwater supply is similar across the Sahel belt, so this statement is suitably general. The specific area of the research (Mali) is mentioned a couple of lines below.

[8] Line11 & 12: "This paper presents a machine learning method to map groundwaterpotential and illustrates it through an application to two regions of Mali". It is poorly structured sentences!

Agreed. The abstract has been rewritten. It now reads:

"Groundwater is crucial for domestic supplies in the Sahel, where the strategic importance of aquifers will increase in the coming years due to climate change. Groundwater potential mapping is a valuable tool to underpin water management in the region, and hence, to improve drinking water access. This paper presents a machine learning method to map groundwater potential in two regions of Mali. A set of explanatory variables for the presence of groundwater is developed first. Scaling methods (standardization, normalization, maximum absolute value and min-max scaling) are used to avoid the pitfalls associated with the reclassification of explanatory variables. Noisy, collinear and counterproductive variables are identified and excluded from the input dataset. Twenty machine learning classifiers are then trained and tested on a large borehole database (n=3,345) in order to find meaningful correlations between the presence or absence of groundwater and the explanatory variables. Tree-based algorithms (accuracy >0.85) consistently outperformed other classifiers. Maximum absolute value and standardization proved the most efficient scaling techniques. Borehole flow rate data is used to calibrate the results beyond standard machine learning metrics, thus adding robustness to the predictions. The southern part of the study area was identified as the better groundwater prospect, which is consistent with the geological and climatic setting. Outcomes lead to three major conclusions: (1) picking the best performers out of a large number of machine learning classifiers is recommended as a good methodological practice; (2) standard machine learning metrics should be complemented with additional hydrogeological indicators whenever possible; and (3) variable scaling helps minimize expert bias".

[9] Line 13: "A set of explanatory variables for the presence of groundwater is developedfirst"
I suggest to replacing the presence of groundwater by groundwater occurrence

Agreed. Fixed. Please see [8].

[10] Line17: "This process identifies noisy, collinear and counterproductive variables andexcludes them from the input dataset":
It is a result details, I suggest deleting this sentence.

On the contrary, this is a crucial methodological detail. This step is relatively often overlooked in machine learning studies, although it is potentially important. We prefer to keep it, although we have rewritten the sentence.

[11] Line 18, 19 & 20: "Tree-based algorithms, including the AdaBoost, Gradient Boosting, Random Forest, Decision Tree and Extra Trees classifiers were found to outperform other algorithms on a

consistent basis (accuracy >0.85), whereas maximum absolute value andstandardization proved the most efficient methods to scale explanatory variables".

I suggest replacing by:

The results shows that the Tree-based algorithms, including the AdaBoost, Gradient Boosting, Random Forest, Decision Tree and Extra Trees classifierswere found to outperform other algorithms on a consistent basis (accuracy >0.85), whereas maximum absolute value and standardization proved the mostefficient methods to scale explanatory variables.

Agreed. Fixed. Please see [8].

[12] Line 22 & 23: "From a methodological standpoint, the outcomes lead to three major conclusions":
I suggest replacing by: The outcomes of this study lead to three majorconclusions

Agreed. Fixed. Please see [8].

Introduction

[13] Line 38 & 39: "Groundwater potential mapping (GPM) is recognized as a valuable tool to underpin planning and development of groundwater resources (Elbeih, 2015)".
I suggest replacing by

Groundwater potential mapping (GPM) is recognized as a valuable tool to underpin planning and exploration of groundwater resources (Elbeih, 2015).

Agreed. Fixed.

[14] Line 41 & 42: "In practice, however, it consists in computing spatially-distributedestimates for a target variable (groundwater potential) based a set of explanatoryvariables"
What are the explanatory variables, you should explain them, I suggest toreplace these sentences by:

However, it consists of computing spatially distributed estimates for a target variable (groundwater potential) based a set of dependent variables such as soil,lineaments, slope, geology, landforms, lithology, and drainage density (Díaz-Alcaide and Martínez-Santos 2019a)

Agreed. Fixed.

[15] Line 42, 43 & 44: "GPM typically relies on existing cartography, digital elevation models obtained from satellite, aerial photographs, satellite imagery and geophysical information (Schetselaar et al., 2007)".
The GPM based on the assembling of data from different sources. I suggestreplacing by:

GPM typically relies on the compilation of data derived from existing maps, aerialphotographs, satellite imagery, and airborne geophysical information (Schetselaar et al. 2008).

Agreed. Fixed.

[16] Line 46: "There are two main approaches to GPM: expert-based decision systems andmachine learning methods".
I suggest replacing by:

Recently, expert-based decision systems and machine learning methods havebeen implemented in many groundwater studies.
Agreed. Fixed.

[17] Line 46 &47: “Expert-based systems have existed for a long time (DEP, 1993)”
I suggest replacing by: Expert-based system methods have been used for a long time(DEP, 1993)

Agreed. Fixed.

[18] Line 52 & 53: Algorithms used in the GPM literature include Mixture DiscriminantAnalysis (Al-Fugara et al., 2020), Random Forest (Kalantar et al., 2019; Moghaddam et al., 2020),
I suggest replacing by:
In literature, The Machine Learning Algorithms used in the GPMstudies include Mixture Discriminant Analysis (Al-Fugara et al., 2020), Random Forest (Kalantar et al., 2019; Moghaddam et al., 2020),

Agreed, but this part of the paragraph has changed at the suggestion of the other reviewer.

[19] Line 58: “GPM works under the assumption that the presence of groundwatercan be partially inferred from surface features”
I suggest replacing by:

The GPM is based on a common assumption is that the groundwater occurrence can be partially inferred from surface features.

Agreed. Fixed.

[20] Line 60 & 61: Supervised classification algorithms are trained to find the associationsbetween these variables and known groundwater data.
The data are trained using the algorithm not the algorithms are trained: Isuggest replacing by:

These explanatory variables are trained using Supervised classification algorithms to findthe associations between them and known groundwater data.

Agreed. Fixed.

[21] Line 64 & 65: add reference.
Because the number of available boreholes to train and test the algorithms is usually “small”, and because the number of explanatory variables can be relatively high, a crucial issue in machine-learning studies is how explanatory variables should be reclassified in order to minimize noise

Agreed. The sentence now reads:

“Because the number of available boreholes to train and test the algorithms is usually “small”, and because the number of explanatory variables can be relatively high, a crucial issue in machine-learning studies is how explanatory variables should be reclassified or grouped in order to minimize noise and decrease the variability of the values of each conditioning factor. The technique of grouping the values of the explanatory variables is widely used. (Gnanachandrasamy et al., 2018; Qadir et al., 2020; Saravanan et al., 2020)

[22] Line 68: add reference
Sometimes the intervals are based directly on expert criteria, which means that a bias may be incorporated from the beginning of the process.

Agreed.

Sometimes the intervals are based directly on expert criteria, which means that a bias may be incorporated from the beginning of the process (Martínez-Santos and Renard, 2020)

[23] Line 71 & 72: The outcomes of machine learning GPM studies are almost invariablyassessed by means of standard big data metrics such as precision, recall, and area under the receiver operating characteristic curve.
I suggest replacing by:

The outcomes of GPM studies using machine learning algorithms are almost invariablyassessed by means of standard big data metrics such as…. And add reference to this observation

Agreed. Fixed. The sentence now reads:

The outcomes of GPM studies using machine learning algorithms are almost invariably assessed by means of standard big data metrics such as precision, recall, and area under the receiver operating characteristic curve (Pradhan, 2013; Naghibi et al., 2016; Chen et al., 2019).

[24] Line 76 to Line 80: Within this context, this research presents two main additions to the literature. In the first place, it explores different scaling methods. The goal is to avoid the pitfalls associated with the reclassification of explanatory variables. Scaling is thus advocated as an essential part of algorithm training since each subsequent procedure depends on the choice of unit for eachfeature (Huang et al., 2015). Furthermore, scaling is expected to transform feature values based on a defined rule, so that all scaled features have the same degree of influence (Angelis and Stamelos, 2000).

I suggest replacing by:

Within this context, this research presents two main additions to the literature. In the firstplace, it explores different scaling methods to avoid the pitfalls associated with the reclassification of explanatory variables. Scaling is thus advocated as an essential part of algorithm training, since each subsequentprocedure depends on the choice of unit for each feature (Huang et al., 2015). Furthermore, scaling is expected to transform featurevalues based on a defined rule, so that all scaled features have the same degree of influence (Angelis and Stamelos, 2000). (Thisis d detail of methodology I propose to add to the methodology section)

Agreed. Fixed. We have moved this paragraph to the methodology section.

Material and methods. Study area

[25] Line 93 to 111: I suggest to add a hydrogeological section or a geologic map to highlightthe aquifers units of the study area

Agreed. Please see [5] above.

[26] Line 89 to 101: “Water in these aquifers is preferentially located in theweathered mantle, and, within this, the lower part is generally more transmissive due to lower clay content. The upper part is less permeable to flow,but can still be important as a groundwater reservoir. Fractures can produce significant quantities of water, although their storage capacity is typically low (Martín-Loeches et al.,2018)”
I suggest replacing by:

In these aquifers, groundwater flows preferentially in the weathered mantle, and, within this, the lower part is generally more transmissive due to lower clay content. The upper part is less permeable to flow but can still be important as a groundwater reservoir wherethe fractures can raise the reservoir permeability although their storage capacity is typically low (Martín-Loeches et al.,2018).

Agreed. This sentence has been rewritten differently based on a comment by the other reviewer.

[27] Line 107: "Some boreholes however exceed 100 m3/hour"
I suggest replacing by:

However, some boreholes yield exceeds 100 m3/hour

Agreed. Fixed.

[28] Line 107 & 108: "The Paleozoic rocks located in the north are determined by fractures that allow water to flow through the sandstone and limestone layers".
I suggest replacing by:

In the north, the fractured Paleozoic rocks allow water to flow through the sandstone andlimestone layers.

Agreed. Fixed.

Borehole database

[29] Line 115: Borehole data were provided by Direction Nationale de l'Hydraulique (2010)
I suggest replacing by:

Borehole data were provided by the National Water Directorate (DNH, 2010)
Agreed. Fixed.

[30] Line 115 to 116: "The database contains 115 information on 5,387 boreholes (3,772 successful and 1,615 unsuccessful), distributed across 1,605 humansettlements".
I suggest replacing by:

The database contains information of 5,387 boreholes (3,772 successful and 1,615unsuccessful), distributed across 1,605 fields.

Agreed. Fixed.

[31] Line 121 to 123: "This can be assumed to be the thickness of the (Courtois et al.,2010). Water table depth
I suggest replacing by:

There is a considerable number of boreholes with a 100% success rate (530), manyvillages are supplied by a single borehole

There seems to be something missing about this comment.

[32] Line 126 to 127: For algorithm training purposes, this raises the question as towhether villages with a small number of boreholes are statistically representative, particularly in cases where the mean yield is low
I suggest replacing by:

This raises the question in the application of algorithm in the choice of training datasets,especially to whether villages with a small number of boreholes are statistically representative, particularly in cases where the mean yield is low

Agreed. Fixed.

[33] Line 145: Figure 3: correct the word classification metrics

Agreed. Fixed.

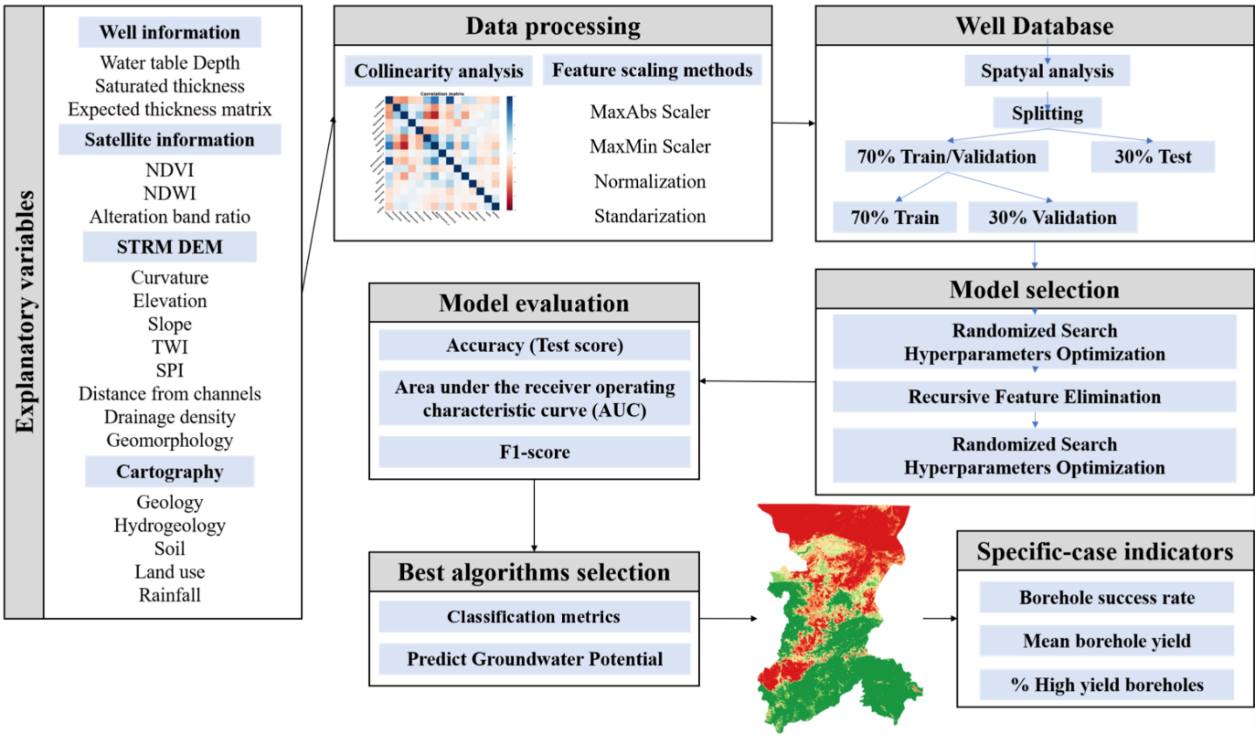

Figure 7. *Conceptual model of the predictive mapping procedure with MLMapper v2.0.*

[34] Line 156 to 157: Sixteen explanatory variables were selected based on an extensive review of the GPM literature (Díaz-Alcaide and Martínez-Santos 2019).

I think to explain in detail this extensive review in the Introduction part

Agreed. The sentence was incorrectly worded. The extensive review was carried out by Díaz-Alcaide and Martínez-Santos (2019). The sentence now reads:

Nineteen explanatory variables were selected from an extensive review of the literature on GPM conducted by Diaz-Alcaide and Martinez-Santos (2019).

[35] Line 161: you should add a description of the main factors that can influence thegroundwater recharge before explaining the description of each used variables or factors in the groundwater potential mapping

Agreed. Please see [6] (first two paragraphs).

[36] Line 162: Geology constrains the presence of groundwater to an importantextent
I think to delete this sentence

Agreed. Fixed.

[37] Line 173: Soils are important in GPM because soil characteristics such aspermeability…
I suggest replacing by:

Soil is important factor to determine the groundwater occurrence ……….

Agreed. Fixed.

[38] Line 174: Soil descriptions of the study area were obtained from the EuropeanSoil Data Centre
You should describe the main soils of the study area types and their characteristics

Agreed. Please see [6]

[39] Line 175 and 176: Integration of land use and land cover is often used in groundwaterpotential mapping studies because human activities alter hydrological dynamics (Díaz-Alcaide and Martínez-Santos, 2019).
I suggest replacing by:

Integration of land use and land cover is often used in groundwater potential mapping studies because Land use changes, which are mostly induced by human activities, affecthydrological dynamics (Díaz-Alcaide and Martínez-Santos, 2019).

Agreed. Fixed.

[40] Line 175 to 180: you should describe the land use of your study area and thedata used for the elaboration of this map
Agreed. We have described the land use and now it reads:

"The study area is clearly divided in terms of land use mainly due to the north-south precipitation gradient. The land use map provided by ESA Climate Change Initiative shows that the southern part is characterized by open broadleaf deciduous forest. The central part is characterized by an alternation of shrublands, mosaics of cropland vegetation and rainfed cropland. West of Bamako, in the sparsely populated mountains, there are forests mixed with shrublands. The northern part of the study area, with less rainfall, is dominated by cropland mosaics and, further north, the landscape is made up of open grasslands, sparse vegetation and bare areas."

[41] Line 182: You should add the reference of used rainfall data
Agreed. Fixed. Suggested by the other reviewer, we added a table containing the reference and source of all data. Rainfall source data was CRU TS 3.21 dataset (Climatic Research Unit at the University of East Anglia).

Explanatory variables	**Scale/resolution**	**Time (dd/mm/yyyy)**	**Source of data**
Alteration Band Ratio	30 meters	07-16/03/2020	Own elaboration from Landsat 8
Clay content	250 meters	N/A	SoilGrids250m 2.0
Curvature	30.53 meters	N/A	Own elaboration from DEM
Saturated thickness	30.53 meters	N/A	Own elaboration from DEM and borehole database
Water table Depth	30 meters	2010	Own elaboration from Borehole database
Distance from channels	30.53 meters	N/A	Own elaboration from DEM
Geology	1:5 million	N/A	British Geologycal Survey
Geomorphology	30.53 meters	N/A	Own elaboration from DEM
Land use	300 meters	2009	ESA Climate Change Initiative
Soil	1:3M	N/A	European Soil Data Centre
Rainfall	0.5°	1950-2009	CRU TS 3.21 dataset (Climatic Research Unit at the University of East Anglia)
Drainaige density	30.53 meters	N/A	Own elaboration from DEM
Thickness matrix	30.53 meters	N/A	Derived from DEM and borehole database
Elevation (DEM)	30.53 meters	23/09/2014	Shuttle Radar Topography Mission (SRTM)
NDVI	30 meters	07-16/03/2020	Own elaboration from Landsat 8
NDWI	30 meters	07-16/03/2020	Own elaboration from Landsat 8
Slope	30.53 meters	N/A	Own elaboration from DEM

SPI	30.53 meters	N/A	Own elaboration from DEM
TWI	30.53 meters	N/A	Own elaboration from DEM

[42] Line 184: Figure 4: you should add the lineaments and faults in the geologicalmap

Agreed. Unfortunately, there is no such map. The available geologic maps are large scale and do not contain the lineaments and faults. We attempted to extract the lineaments automatically from the DEM, but the large area of the study region led to unsuccessful results.

[43] Line 191 & 192: DEMs are relevant because shallow groundwater flow and infiltration are partially conditioned by surface features and parameterized by properties that can be extracted from the surface data (Elbeih, 2015)
I suggest replacing by:

The topography is a relevant factor in groundwater distribution, storage, and flow, as well as surface runoff and infiltration are partially conditioned by surface features and parameterized by properties that can be extracted from thesurface data (Elbeih, 2015)

Agreed. Fixed.

[44] Line 197: The topographic wetness index
I suggest replacing by:

The Topographic Wetness Index (TWI)

Agreed. Fixed.

[45] Line 243: Figure 6. Explanatory variables used to predict the GPM: a) water table depth (meters) b) slope (degree) c) curvature d) borehole yield (m3/h) e) normalized difference vegetation index (NDVI) f) normalized difference waterindex (NDWI) g) alteration band ratio (B6/B7) h) Drainage density i) Stream power index (SPI) j) topographic wetness index (TWI) k) Claycontent 245 (g/kg) l) rainfall (mm/year)

What is the difference of the figure 6g (alteration band ratio (B6/B7)) and the figure 6k (Clay content); in the text it means the same information line 230 to 233: This layer provides information on clay content on the surface and the relationship with infiltration. Clay content on the surface is calculated as per Eq. 5, where B6 is theshort-wave infrared 1 and B7 the short-wave infrared 2.

Agreed. The text might be slightly confusing. Clay content layer was obtained by state-of-the-art machine learning methods that use global soil profile information and covariate data to model the spatial distribution of soil properties around the world. This layer provide information about the clay content in the top two meters of soil, i.e. information about subsurface clay content and was obtained from SoilGrids (Poggio and de Sousa, 2020). In contrast, the alteration band ratio was used in this study for its ability to map clay minerals using bands 6 and 7 of Landsat 8 (Ourhzif et al., 2019). This layer provides information about the surface clay content.

If our manuscript continues in the revision process, we will rewrite the information about these layers in the explanatory variables section.

[46] Line 267: reference of equation 6

Agreed. Fixed.

[47] Line 273: reference of equation 7

Agreed. Fixed.

[48] Line 380 to 400: I find this paragraph should be added to the introductionsection to explain the use of used algorithms in literature

Agreed. If our manuscript continues in the revision process, we will add this paragraph to the introduction section.

[49] Line 437: Classifier outcomes were extrapolated to produce groundwaterpotential maps
What you want to say it is not clear!

Agreed, the text might be slightly confusing. We refer to the fact that the algorithms were trained and validated with the information from the borehole database. In contrast, to develop the final groundwater potential maps, it's necessary to know the distribution of the explanatory variables throughout the study area. Therefore, we discussed extrapolating the patterns learned from the borehole database to the entire study area to produce the groundwater potential maps.

[50] Line 437 to 438: Figure 9 shows the groundwater potential predictions renderedby each of the five best-performing algorithms under the two most effective scaling methods

I suggest adding the abbreviations of used algorithms and scaling methods betweenparentheses

Agreed. Fixed.

[51] Line 447: The agreement map (Fig. 10) allows for an analysis of discrepanciesamong the best performing algorithms.
What you want to say about the agreement map!

Agreed. The description regarding the source of this map was in the supervised classification routine subsection:

"Each algorithm operates differently and relies on a different combination of explanatory variables, which inevitably leads to discrepancies in the predictions. In order to analyse the degree of agreement between the classifiers, an ensemble map is developed by computing the arithmetic mean at the pixel scale of those algorithms exceeding 0.85 predictive accuracy. Green pixels mean that all the best-performing algorithms agreed on a positive groundwater potential outcome (arithmetic mean = 1). Conversely, red zones represent those pixels where all the best-performing algorithms agreed on a negative groundwater potential (arithmetic mean = 0). Intermediate colours represent various degrees of agreement among the algorithms."

[52] Line 455: Figure 9. Mapping outcomes of the top five supervised classification algorithmsfor the two best performing scaling methods. At the top the MaxAbs scaling method, below it the standardized scaling method. From left to right: AdaBoost classifier, GradientBoosting classifier, Random Forest classifier, Decision Tree classifier and Extra Trees classifier.
I suggest to add number or letter for each map like:
AdaBoost classifier, (b) Gradient Boosting classifier, (c) Random Forest classifier, (d)Decision Tree classifier and (e) Extra Trees classifier.
Agreed. Fixed.

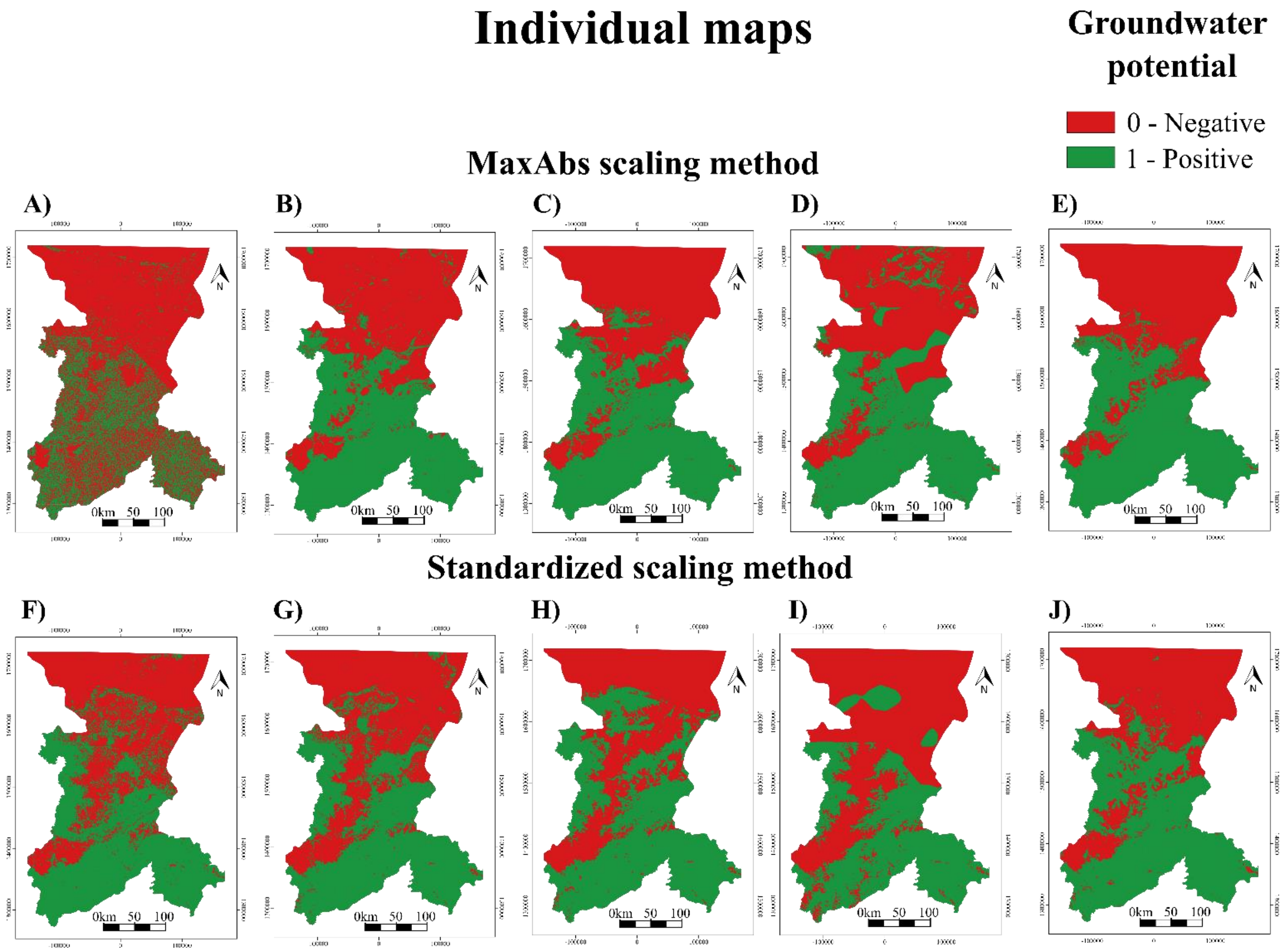

Figure 10. Mapping outcomes of the top five supervised classification algorithms for the two best performing scaling methods. At the top the MaxAbs scaling method: A) AdaBoost classifier B) Gradient Boosting classifier C) Random Forest classifier D) Decision Tree classifier E) Extra Trees classifier. below it the standardized scaling method: F) AdaBoost classifier; G) Gradient Boosting classifier H) Random Forest classifier I) Decision Tree classifier J) Extra Trees classifier.

[53] Line 492 to 494: "On a final note, the literature features few examples of groundwater potential studies in the study area. Perhaps the only systematic precedent is the one carried out by Díaz-Alcaide et al. (2017). These authors performed a national-scale assessment of groundwater potential for the Republicof Mali based on the same borehole database that has been used in this research".

This is a literature review about similar studies in pilot area, I suggest to add in the Introduction section

In this case we attempt to place our results in the context of other studies of the same area, which is suitable for the discussion.

On a final note, we would like to thank Reviewer #2 again for a thorough review of our manuscript. We hope our answers will be enough to merit publication in HESS.

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