Linking soils and human health: geospatial analysis of ground-sampled soil data in relation to community-level podoconiosis data in North West Cameroon

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Received 24 June 2020; revised 26 October 2020; editorial decision 29 October 2020; accepted 2 November 2020

Background: Podoconiosis is a form of leg swelling, which arises when individuals are exposed over time to red clay soil formed from alkaline volcanic rock. The exact causal agent of the disease is unknown. This study investigates associations between podoconiosis disease data and ground-sampled soil data from North West Cameroon.

Methods: The mineralogy and elemental concentrations were measured in the soil samples and the data were spatially interpolated. Mean soil values were calculated from a 3 km buffer region around the prevalence data points to perform statistical analysis. Analysis included Spearman’s rho correlation, binary logistic regression and principal component analysis (PCA).

Results: Six elements, barium, beryllium, potassium, rubidium, strontium and thallium, as well as two minerals, potassium feldspar and quartz, were identified as statistically related to podoconiosis. PCA did not show distinct separation between the spatial locations with or without recorded cases of podoconiosis, indicating that other factors such as shoe-wearing behaviour and genetics may significantly influence podoconiosis occurrence and prevalence in North West Cameroon.

Conclusion: Several soil variables were statistically significantly related to podoconiosis. To further the current study, future investigations will look at the inflammatory pathway response of cells after exposure to these variables.

Keywords: Cameroon, geospatial, interpolation, mineral, podoconiosis, soil

Introduction

Podoconiosis is a non-infectious geochemical disease, affecting individuals exposed to red clay soil derived from alkaline volcanic rock. The disease causes asymmetrical bilateral swelling of the lower legs. The exact causal agent in the soil is unknown, but has previously been linked to elements such as aluminium, zirconium, beryllium and silica, as well as minerals such as quartz. However, recent studies have identified that a genetic aspect of the disease exists that affects individual susceptibility.
Figure 1. Map of Africa, with two inset maps of Cameroon. The inset map shows the location of soil and community-level podoconiosis sample locations.

established that where the clay fraction exceeded 25% in the top soil, the probability of podoconiosis increased; conversely, where the clay fraction exceeded 40% in the top soil, the probability of podoconiosis decreased. Another notable example of a large-scale study used samples from an online database representing bedrock from five regions of Africa known to be associated with podoconiosis. The study also employed a sixth region with the Hawaiian islands as a control. In the study, weight percentage data for oxides within the samples from across the six studied regions were analysed using a combination of principal component analysis (PCA), discriminant function analysis and analysis of variance, with results suggesting that a unique alkaline- and silicon-rich geochemistry underlies regions associated with podoconiosis. Large-scale studies such as these have proved useful in identifying broad soil and geochemical type associations with podoconiosis over large areas; however, they cannot discriminate small-scale variations at local levels. Smaller scale podoconiosis studies have previously investigated the associations between detailed ground-sampled soil data and community-level podoconiosis data in northern Ethiopia and in Kenya. The Ethiopia study identified several statistically significant variables linked to prevalence, including quartz, mica and smectite content levels. The Kenya study identified, through multivariate modelling, and while adjusting for the frequency of participants wearing shoes, that iron was significantly associated with podoconiosis. Additionally, when the model was controlled for iron, aluminium concentrations became significant.

Establishing consistent associations between environmental variables and podoconiosis has been problematic and performance throughout the literature has been variable, particularly when analysed at different spatial scales. Previous large-scale podoconiosis studies have indicated that climate variables can be important predictors of podoconiosis; however, in the current study, the focus will remain solely on high resolution soil data due to the limited climatic variability across the study area.

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This novel study develops previous research, particularly for North West Cameroon, by aiming to increase both the spatial resolution of the investigation and detail of soil analysis. The study relates community-level podoconiosis data, collected by community health implementers (CHIs), with mineralogical and elemental data obtained via x-ray diffraction (XRD) and inductively coupled plasma mass spectrometry (ICP-MS), respectively.

Materials and Methods

Study area

This study was conducted in the North West Region of Cameroon (Figure 1) between latitudes of 5°53’ to 6°19’ and longitudes of 9°42’ to 10°18’. The North West Region of Cameroon is a podoconiosis-endemic region. The main occupation in North West Cameroon is farming.

Data collection

Podocoanosis data collection

The disease data were collected as part of a previous study in which the collection strategy is reported. The study consisted of individuals aged >18 y and those who had lived in the area...
Figure 2. Map highlighting the spatial contiguity and location of the soil and podoconiosis community-level sample locations in the North West Region of Cameroon.

Soil data collection

One hundred and fifty-two sampling sites were spaced 4.5 km apart in a gridded formation. Samples were taken at the centre of each grid square. At each soil sampling site, GPS coordinates (WGS 84, decimal degrees), elevation (m), vegetation type and fertiliser/insecticide usage were recorded. Any vegetation or rocks were removed from the surface and a rock hammer was then used to mix soil to a depth of 10 cm. Any large roots, rocks or stones >0.5 cm in diameter were removed and a trowel was used to collect one scoop (approximately 300 g) of soil, which was stored in a sample bag.

This process was then repeated twice at each sampling site, at 10 paces due west and 10 paces due east from the original sampling point. At each sampling location the completed samples were all mixed into the same sample bag.

In addition to this standard sampling approach, 10 random grid squares featured 5 extra sampling sites. This was implemented to capture the soil variability at a greater resolution; the format of this collection is shown in Figure 3.

The central blue circle represents the original soil sample and a–e represent the five additional sampling points.

However, some samples were not collected, due to inaccessibility of sample locality, or were deemed missing, resulting in 194 soil samples being collected out of the planned 202 samples (Figure 2).

Analysis of the chemical element constituents of the 194 soil samples was performed using ICP-MS. The total element content was obtained for 0.25 g subsamples of soil digested using a mixture of hydrofluoric, perchloric and nitric acids. Semiquantitative XRD was employed to derive the mineralogical content of the soil samples. A subsample of 100 of the 194 soil samples were tested using XRD. XRD and ICP-MS analysis was completed by the British Geological Survey. The soil variables measured can be found in the supplementary data Tables 1–3.

Data preparation

Spatial interpolation of soil variables

High resolution soil sampling over large areas is not always achievable, due to logistical, temporal and financial constraints. Spatial interpolation is therefore a vital tool that is frequently used for at least 10 y. The census was carried out by CHIs, who visited all the households in the selected communities, registering every individual in each household and screening those individuals for podoconiosis. Research team members re-examined the cases considered positive by CHIs. The data included global positioning system (GPS) coordinates of the community, podoconiosis prevalence data (the proportion of the community with the disease) and a binary variable representing presence or absence of the disease, which will be referred to as the occurrence data. A correction factor of 48.5 was applied to the prevalence data to account for overdiagnosis of podoconiosis during data collection by CHIs; 168 sampling points were selected and utilised in this study due to their spatial contiguity with the soil sampling data points (Figure 2).
for the mapping of soil properties over large spatial extents.\textsuperscript{17} Although several authors have assessed and compared different interpolation methods for soil data modelling, no consensus exists on the best method.\textsuperscript{17,18} Four spatial interpolation techniques commonly employed for soil mapping were examined in this study to determine the effectiveness of each to represent the spatial distribution of the soil variables. These methods included inverse distance weighting (IDW),\textsuperscript{18} ordinary kriging (OK),\textsuperscript{19} empirical Bayesian kriging (EBK)\textsuperscript{20} and universal kriging (UnK).\textsuperscript{21} These interpolation methods were carried out using ArcGIS version 10.5.1 (ESRI, Redlands, CA, USA). The ‘leave-one-out’ cross validation method was utilised to assess model performance. Prediction error statistics were used for model selection, which can be found in supplementary data table 4, and the workflow model followed can be found in supplementary data figure 1.

**Statistical analysis**

**Bivariate analysis**

The associations between the soil and disease data were analysed using bivariate analysis.

**Spearman’s rho correlation analysis**

Spearman’s rho correlation analysis was carried out between mean soil variable values from the interpolation surface calculated using the 3 km buffer zones and the corresponding podoconiosis prevalence value. In total, 168 data points were used for the correlation analysis. Variables with $p > 0.05$ and variables with a significant negative correlation were removed from the subsequent multivariate analysis.

**Binary logistic regression analysis**

Logistic regression analysis was carried out between mean soil variable values from the interpolation surface calculated using the 3 km buffer zones and the corresponding binary variable representing disease occurrence. Logistic regression moves beyond correlation analysis because, instead of using prevalence (which measures the amount of podoconiosis in relation to population), it utilises occurrence data. By analysing occurrence data, the soil variables can be examined to predict how a unit increase of the individual soil variable affects the likelihood of a community
having at least one case of podoconiosis. In total, 168 data points were used for the analysis. Variables with \( p > 0.05 \) and variables with \( \text{OR} < 1 \) were removed from the subsequent multivariate analysis.

**Multivariate analysis**

**PCA**

PCA was utilised to reduce the dimensionality of the soil element and mineralogical data, while retaining the variation present in the original data set. This was completed by a linear transformation of the original data to create a set of new orthogonal variables called principal components.

The PCA included those soil variables identified from the bivariate analysis as statistically significant (\( p < 0.05 \)) with either a positive correlation or \( \text{OR} > 1 \). To visualise the underlying structure of the data, a biplot was created and ellipses of 95% confidence were produced representing areas with podoconiosis (presence) and areas with no identified cases of podoconiosis (absence).

**Multiple testing**

Within this study, multiple testing corrections were applied due to the large number of individual tests performed; however, all (premultiple testing) significant results were included in the subsequent PCA. This approach was implemented as the aim of this study was not to state that the statistically significant variables are the ‘causal agents of podoconiosis’, but rather to identify potential variables, which could be investigated in subsequent analysis.

**Results**

**Spatial interpolation outcome**

For several variables it was not possible to perform spatial interpolation, due to their excess zero values and the inability to produce a reliable interpolation surface. Zero values occurred due to the absence of the variable or due to the sensitivity of the testing procedures employed. Variables affected by these issues included the minerals anatase, cristobalite, tridymite, amphibole, olivine, chromite, ilmenite, smectite, vermiculite and hydrobiotite.

Using prediction error statistics, interpolations associated with each technique were examined then chosen for further processing (see Figure 4 for an example interpolation surface). These included the following surfaces: 0 from IDW, 2 from UnK, 20 from OK and 42 from EBK. The prediction error statistics for these surfaces can be found in the supplementary data table 5.

**Spearman’s rho correlation outcome**

From correlation analysis of the 3 km buffer zones around the disease data coordinates, it was identified that the mean soil values for the chemical element variables barium (Ba), beryllium (Be), potassium (K), rubidium (Rb), strontium (Sr) and thallium (Tl), as well as those of the mineral variable potassium feldspar (K-feldspar), were positively correlated with the prevalence of podoconiosis (Table 1).

**Binary logistic regression outcome**

From binary logistic regression, the mean soil values identified from the 3 km buffer zones around the disease data coordinates...
gests that with a unit increase of these variables, the likelihood
variation of the data set, respectively. PC3 accounted for 8.6%
3 km buffer zones and the corresponding
PC1 and PC2 (Figure 5).
PCA was utilised to identify any underlying patterns in the data
by creating a biplot of the scores and variable loadings for the
principal components PC1 and PC2 (Figure 5).
The first two PCs account for 64.6% and 17.1% of the total
variation of the data set, respectively. PC3 accounted for 8.6%
eigenvector, suggesting they are highly correlated with each other. The
variables with the greatest eigenvectors on the horizontal axis
therefore with the greatest weighting on PC1 include the vari-
ables K-feldspar, Sr, K, Rb, Ba and Tl. The variables with the great-
est eigenvectors on the vertical axis, and therefore with the great-
est weighting on PC2, include the variables quartz and Be.
From a visual inspection of the PCA, it appears that there is no
distinct separation between the communities with at least one
case of podoconiosis and communities with no recorded cases.
However, with the 95% confidence ellipses added, the data do
show a separation, on both component axes, between the dis-
ease presence ellipses as the selected soil variables increase in
value.

**Table 1.** Correlation between the mean soil variable values
extracted from the 3 km buffer zones and the corresponding
podoconiosis prevalence data. Spearman’s rho correlation coeffi-
cient, 95% CIs and p-value. Sample size 168. Only variables with
p-value<0.05 are included in the table. Variables are shown by
their abbreviated names.

| Variable       | Correlation coefficient | 95% CIs          | p    |
|----------------|-------------------------|------------------|------|
| **Elements**   |                         |                  |      |
| As             | -0.200                  | -0.343 to -0.049 | 0.009|
| Ba*            | 0.230                   | 0.079 to 0.370   | 0.003|
| Be*            | 0.194                   | 0.043 to 0.337   | 0.012|
| Cd             | -0.202                  | -0.345 to -0.051 | 0.008|
| Ce             | -0.191                  | -0.334 to -0.04  | 0.013|
| Cr             | -0.205                  | -0.347 to -0.053 | 0.008|
| Fe             | -0.154                  | -0.300 to -0.002 | 0.046|
| Gd             | -0.176                  | -0.320 to -0.024 | 0.022|
| Hf             | -0.157                  | -0.302 to -0.005 | 0.042|
| K*             | 0.182                   | 0.03 to 0.326    | 0.018|
| LOIa           | -0.212                  | -0.354 to -0.061 | 0.006|
| Lu             | -0.154                  | -0.299 to -0.001 | 0.047|
| Mo             | -0.162                  | -0.307 to -0.01  | 0.036|
| Nb             | -0.176                  | -0.320 to -0.024 | 0.022|
| Nd             | -0.173                  | -0.317 to -0.021 | 0.025|
| P              | -0.266                  | -0.403 to -0.117 | 0.0001|
| Pr             | -0.170                  | -0.314 to -0.018 | 0.028|
| Rb*            | 0.161                   | 0.009 to 0.306   | 0.037|
| Sm             | -0.173                  | -0.307 to -0.021 | 0.025|
| Sr*            | 0.155                   | 0.003 to 0.301   | 0.044|
| Ta             | -0.193                  | -0.336 to -0.042 | 0.012|
| Ti             | -0.202                  | -0.344 to -0.05  | 0.009|
| Ti*            | 0.192                   | 0.041 to 0.335   | 0.013|
| Tm             | -0.170                  | -0.314 to -0.018 | 0.028|
| V              | -0.252                  | -0.391 to -0.103 | 0.001|
| Zr             | -0.160                  | -0.305 to -0.008 | 0.038|
| **Minerals**   |                         |                  |      |
| Goethite       | -0.152                  | -0.297 to 0.000  | 0.049|
| K-feldspar*    | 0.154                   | 0.002 to 0.300   | 0.046|

*aLOI=loss on ignition represents organic matter content.
*Variables with a statistically significant positive correlation coefficient.

for both Ba and quartz had a significant OR>1 (Table 2). This sug-
gests that with a unit increase of these variables, the likelihood
that an area has at least one case of podoconiosis increases.

**PCA outcome**
PCA was utilised to identify any underlying patterns in the data
by creating a biplot of the scores and variable loadings for the
principal components PC1 and PC2 (Figure 5).

The first two PCs account for 64.6% and 17.1% of the total
variation of the data set, respectively. PC3 accounted for 8.6%
eigenvector=0.69) of the variation of the data. Therefore, PC3 and
subsequent PCs, with decreasing eigenvalues, were not investi-
gated in this study as they explained low variation of the data set
and would be unlikely to identify any patterns.

In the PCA ordination, the communities with at least one case
of podoconiosis are represented by blue triangles and those com-
munities with no recorded cases are represented by red dots.

The PC1 axis highlights a clustering of the positive eigenvector-
s, suggesting they are highly correlated with each other. The
variables with the greatest eigenvectors on the horizontal axis
and therefore with the greatest weighting on PC1 include the vari-
ables K-feldspar, Sr, K, Rb, Ba and Tl. The variables with the great-
est eigenvectors on the vertical axis, and therefore with the great-
est weighting on PC2, include the variables quartz and Be.

Discussion

**Spatial interpolation**
Continuous ground-sampled surface soil data were not available,
and therefore, to co-locate and extract meaningful soil values for
each prevalence data point, interpolation modelling was neces-
sary using the existing soil sample data set.

In this study, and following independent validation, EBK was
identified as the most suitable method for 42 of the 64 soil vari-
able. However, it should be noted that regarding the prediction
error statistics, OK performed almost as well in most cases. This
finding is consistent with other studies.23 The suggested advan-
tage of EBK over the two other kriging methods (UnK and OK) is
in its ability to account for the error introduced by estimating the
semivariogram model through repeated simulations.

**Buffered spatial selection**
Previous studies comparing environmental and podoconiosis
data have not considered the movement of people directly.2,5
Instead, these studies either compared the soil variables beneath
the disease data coordinates 5 or compared soil variables col-
lected from the households in the study.2 These studies are
ultimately reliant upon geolocation accuracy, village boundaries
and sedentary lifestyles.2,5 However, the buffer approach imple-
mented in this study considered the geolocation accuracy of the
prevalence data points and the movement of people in this area of
Cameroon within a fixed radius.

Statistical analysis outcome
The PCA and biplot revealed no discrete groupings of soil compo-
sitions with respect to communities in which podoconiosis was
present or absent. This suggests that the relationship between
soil and this disease is likely complex and nuanced, moreover,
areas can have similar soil compositions but different occurrence
values. However, the results do indicate separation between the
disease occurrence ellipses as the selected soil variables increase in value and that these variables represent disease covariates. This further supports the literature and may indicate that other factors such as shoe-wearing behaviour, foot washing and genetics may play a significant role in podoconiosis occurrence. The genetic and behavioural influence of the disease may also indicate why correlation values for the significant variables were moderate to weak. Although statistical analysis was robust, the weak to moderate outcomes could also be attributed to inaccuracies in the CHIs' collection of prevalence data and the common occurrence of initial misdiagnosis of podoconiosis. Misdiagnosis may have occurred due to the occurrence of lymphatic filariasis in North West Cameroon as oedema of the foot and lower leg is frequently fatal lung disease, chronic beryllium disease (chronic berylliosis), and is listed as a class A Environmental Protection Agency (EPA) carcinogen.

K has previously been identified as occurring in mineral particles of elephantiasis nodes, but Price and Henderson were unable to report if there was a significant difference between non-elephantiasis nodes. Other studies reported an increase of K in podoconiosis-endemic soils. However, it is inferred that K is an unlikely pathological variable at small-scale absorption as K is an essential constituent of the body.

In the Ethiopia study, quartz was significantly associated with the prevalence of podoconiosis in ground-sampled soil variables. Quartz is a very common mineral, occurring in almost all rock types and, due to its resistance to weathering, in most soils. Although inhalation of very fine-grained (<10 µm) forms of quartz may cause silicosis, the relationship between quartz and podoconiosis is perhaps surprising considering quartz's generally inert chemical behaviour. However, its relative hardness (7 on the Mohs scale) may result in increased skin abrasion, facilitating the entry of more toxic elements. As previously suggested, repeated exposure to quartz could worsen stratum corneum degradation and enable particles to penetrate the skin.

In Ethiopia, feldspar was reported to have a statistically significant lower proportion in endemic compared with non-endemic soils. However, it should be recognised that the feldspar identified in the Ethiopian study could represent multiple types of feldspar other than the K-feldspar measured in the current study. K-feldspar is a common mineralogical component of igneous and metamorphic rocks in particular, but it is also found in sedimentary rocks and therefore soils derived from all three bedrock types. The association between Ba, K, Rb, Sr, Ti and K-feldspar is well

### Table 2. Binary logistic regression between the mean soil values extracted from the 3 km buffer zones and the corresponding binary occurrence of podoconiosis. The coefficient, standard error, Z-value, p-value, OR and 95% CIs. Sample size 168. Only variables with p-value <0.05 are included in the table. Variables are shown by their abbreviated names.

| Variables | Coefficient | Std. error | Z-value | p | OR 95% CI |
|-----------|-------------|------------|---------|---|-----------|
| Ba*       | 0.002       | 0.001      | 2.28    | 0.017 | 1.002 to 1.003 |
| LOIa       | −0.184      | 0.062      | −2.98   | 0.002 | 0.832 to 0.939 |
| P         | −0.002      | 0.001      | −2.28   | 0.02   | 0.999 to 1.000 |
| Th        | −0.027      | 0.013      | −2.05   | 0.039 | 0.973 to 0.999 |
| V         | −0.016      | 0.006      | −2.5    | 0.011 | 0.985 to 0.997 |
| Minerals  |             |            |         |      |           |
| Amorphous | −0.054      | 0.026      | −2.06   | 0.037 | 0.947 to 0.998 |
| Quartz*   | 0.091       | 0.04       | 2.29    | 0.018 | 1.095 to 1.184 |

*aLOI=loss on ignition represents organic matter content.

Variables with a statistically significant OR > 1.
established, as K forms a major component (11–14%) of this group of minerals, and Ba, Rb, Sr and Tl all readily substitute for K, as they have similar ionic radii.30

Finally, Rb and Tl have not been previously identified as potentially associated with podoconiosis. To the knowledge of the authors, no previous studies have examined these variables in relation to podoconiosis.

From this study it is further highlighted that elements and minerals identified as potential disease covariates or triggers of podoconiosis can vary from one place to another. It should be acknowledged that factors describing the soil physical properties, such as the texture and structure of the soil, or complex interactions between elements and minerals, could have a greater impact on the risk of podoconiosis than a single element or mineral. This potentially complex interaction could explain why there is no consensus on single elements or minerals from these studies across multiple countries. It is recommended that future studies should also investigate the physical properties of the soil in relation to podoconiosis.

**Conclusions**

From the analysis presented in this study, several soil variables were statistically identified as significantly related to podoconiosis. It is, however, not clear if the variables identified can be suggested as disease covariates or as causal agents of the disease. The weak to moderate strength of these relations could be impacted by other influences such as genetic variation and shoe-wearing behaviour, as well as the errors inferred from spatial interpolation. To further the current study, future investigations should consider the inflammatory pathway response of cells to exposure of these significant variables. This would further our understanding as to whether these soil variables have a potential role in the pathogenesis of podoconiosis.

**Supplementary data**

Supplementary data are available at *Transactions* online.
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