Exploring the use of multiple covariates and machine learning in disaggregating complex soil maps

MSc Thesis

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Abstract

Soils have an important role in providing ecosystem services to plants, animals and humans. Information about soils is often exchanged using soil types. In this way information about a whole set of soil properties can be communicated. However, soil maps using soil types often contain complex mapping units. Complex mapping units are map features that incorporate multiple soil types with their distributions and have the advantage that at small scales still all the soil information can be included. The problem with these complex mapping units is that it is unknown where the soil types are located in the mapping unit. This makes it hard to interpret these soil maps. To overcome this, complex mapping units are often converted to simple mapping units. The most common method is to generalise the whole mapping unit with the dominant soil type, allowing the loss of all the spatial variation. To prevent the loss of the spatial variation, a recent development uses a catena based on one covariate to disaggregate a complex mapping unit. However, disaggregating using one covariate or the dominant soil type is not ideal.

In this study, two methods are proposed to disaggregate soil maps with complex mapping units based on multiple covariates. Both methods use machine learning, multiple covariates and detailed soil maps. Their difference is based on their usage of complex mapping units. The first method, called the loosely enforced method, uses the soil type distributions as a covariate for the machine in the same way as the other environmental covariates. This method disaggregates the mapping unit be giving each cell the soil type with the highest probability. The second method, called the strictly enforced method, uses only the environmental covariates in the machine and predicts the probability for all the soil types. An algorithm disaggregates each cell by using the probabilities and the distribution of the soil types.

To explore the potential, several disaggregation models were developed, using the two disaggregation methods, two datasets and two learning algorithms for the machine, i.e. multinomial logistic regression and tree ensemble. When the disaggregation methods were validated, accuracies of 50 till 60% could be reached. Validating the strict enforced method is more difficult as a whole area has to be left out of the training and the accuracies are hard to interpret. When the disaggregation methods are used on large areas outside training areas, especially the loosely enforced method got it difficult.

The ideal option to disaggregate complex mapping units is the strict enforced method, nevertheless improvements have to be made to use in it in a feasible way.

Introduction

Soils play a valuable role in contributing ecosystem services, like providing nutrients to plants and storing carbon as soil organic matter (Palm et al. 2007). An efficient way to exchange information about soil can be the usage of soil types. Soil types give information about a whole range of different soil properties and can connect this information to possible applications of the soil. Many countries in the world have their own soil classification system, but two classification systems are often used internationally: Soil Taxonomy, which is developed by the Soil Survey Staff (1999) and has at the first level 12 soil orders and the World Reference Base for Soil Classification (WRB), which is developed by the FAO as a correlation umbrella for all the different classification systems by and has at the first level around the 30 Reference Soil Groups (RSG) (IUSS Working Group WRB 2015).

Soil maps based on an explanatory soil survey often contain complex mapping units. These complex mapping units contain several soil types and their distribution in the mapping unit. The advantage of using complex mapping units is that at even small scales still all the soils that occur can be represented. However, the soil types in one complex mapping unit can have very different properties and the exact spatial distribution in the unit is not known. This makes it more difficult to interpret soil data especially for interested people outside the field of soil science, as advanced soil knowledge of the area is needed to interpret the complex mapping units. Also for spatial models using soil maps as input, it is difficult to use complex mapping units as they can often use only 1 soil type at 1 location.

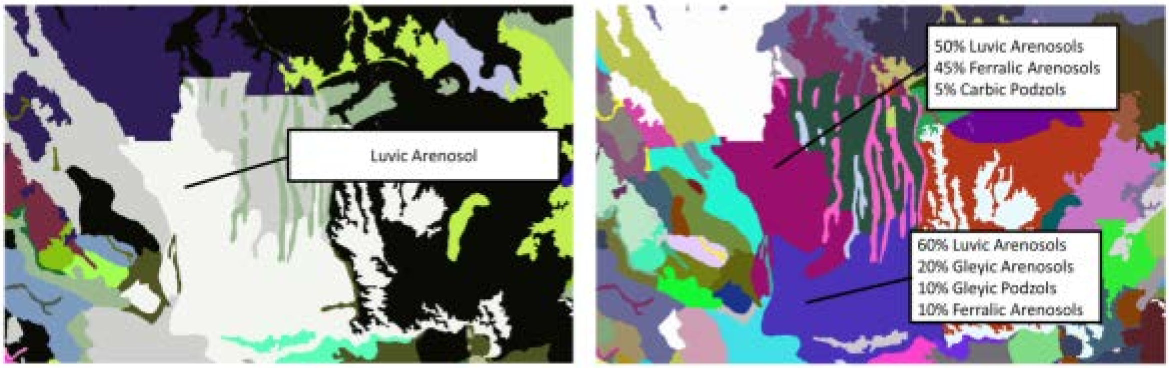

Figure 1 The left picture shows the dominant soil types, while in the right picture every mapping unit has his own colour and can be seen that not only the dominant soil type occurs in a mapping unit.

Well-known examples of soil maps with complex mapping units are the STATSGO2 for the United States, the SOTER maps for different regions around the world and at a global level the Harmonized World Soil Database (HWSD). The HWSD is the successor of the Soil Map of the World and its development started in the 1960's and 1970's by the FAO and UNESCO (Selcer 2015). Their goal was to make global soil data better available by creating a uniform soil dataset. The HWSD contains over 15 000 soil mapping units and is freely accessible (Fao/Iiasa/Isric/Isscas/Jrc 2009). Around 20% of the mapping units in the HWSD contains 1 soil type and are thus simple mapping units. The other 80% are complex mapping units. On average, the HWSD contains 2.6 soil types per mapping unit, with a maximum of 10 soil types (Figure 2).

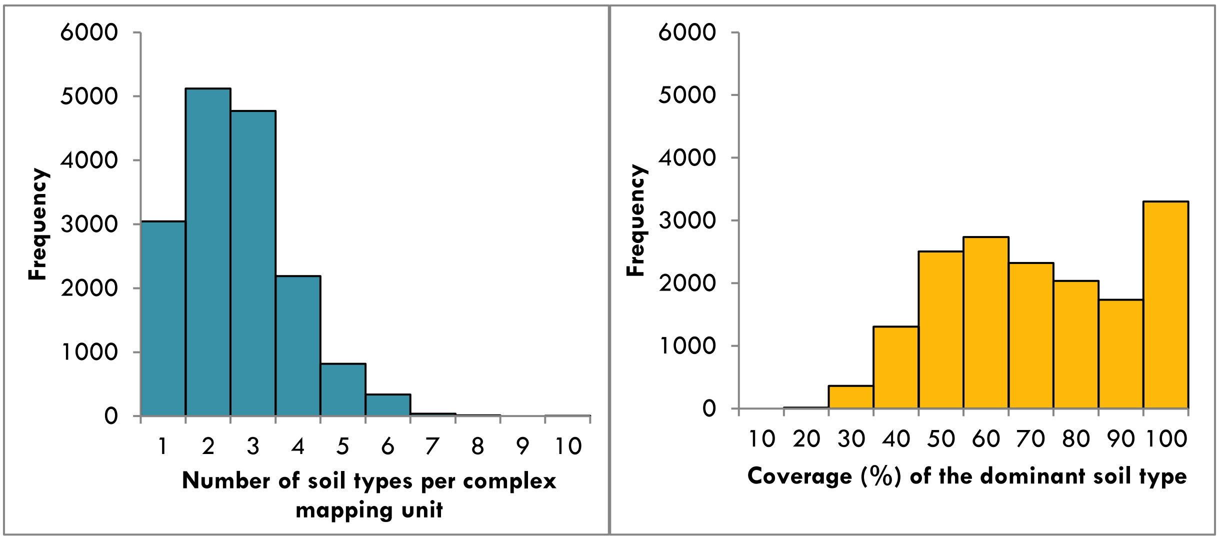

Figure 2 The histogram on the left shows the amount of soil types per complex mapping unit, with on average 2.7 soil types per mapping unit. The histogram on the right shows the coverage in percentage of the dominant soil type in the complex mapping unit with an average of 70%.

Often complex mapping units in a soil map are difficult to use and are converted to simple mapping units. Two methods are often used now: the dominant soil type method. The most common method is the dominant soil type method (DST). With this method the soil type that occurs the most in the complex mapping unit, called the dominant soil type, is chosen to represent the complete simple mapping unit with only one soil type. In this way, it generalises the complex mapping unit into a simple mapping unit. This method has the advantage that it is very easy to process and to understand the conversion. However, the main disadvantage is that it neglects the variation of soil types in a complex mapping unit. This may not be a large problem for complex mapping units with a very dominant soil type, but for mapping units where there is much variation the generalisation can cause a large error when converting to simple mapping units.

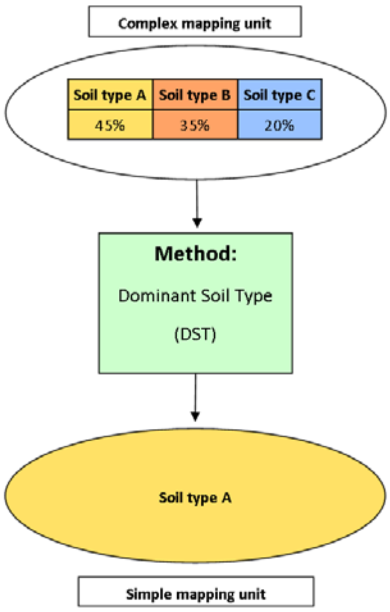

Figure 3 Schematic overview of the dominant soil type method (DST) which generalises the simple mapping unit with the soil type that covers the largest part of the complex mapping unit.

A method that is developed recently to respect the variation of soil types in complex mapping unit is the catena method. The catena method uses a standardized catena based on one covariate. The soil types are ranked, often using expert knowledge. The disaggregation is based on the catena, the covariate and the distribution of the complex mapping unit. The soil type that has the highest ranking in the catena will get the fraction of the area in the mapping unit that has the highest values for the covariate. This continues with the soil type ranked second getting the fraction of the mapping unit that has the highest values for the covariate and still left. This continues until all soil types are done and the product will be a complex mapping unit disaggregated into simple mapping units respecting the original distribution of the complex soil map. In this study S-World of Stoorvogel et al. (2017) is used for the catena method. S-World uses a catena based on elevation, i.e. a toposequence, and is based on the HWSD.

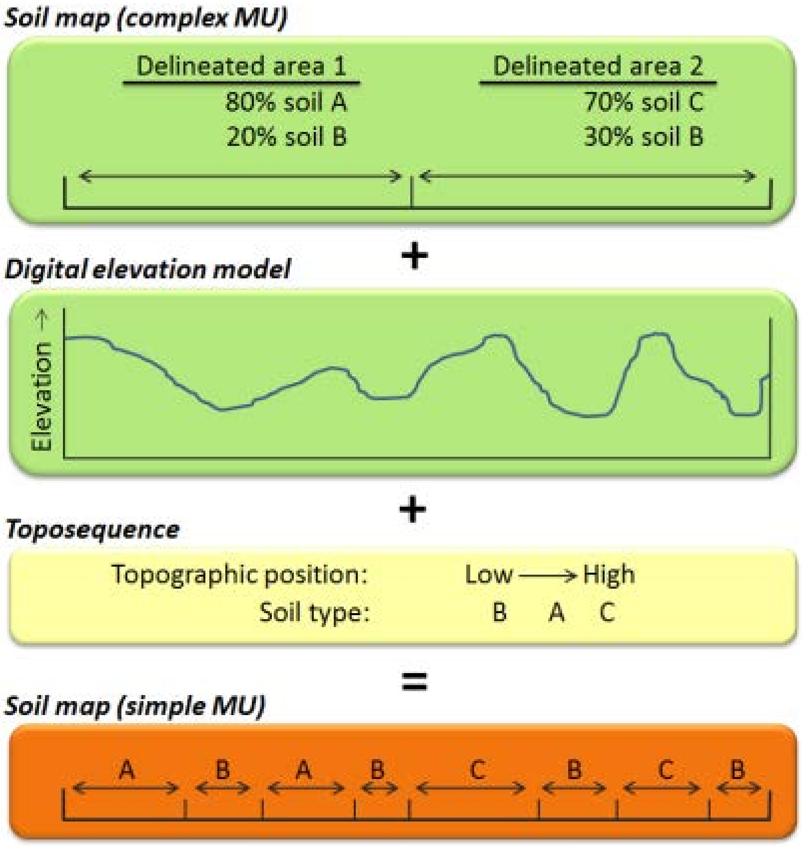

Figure 4 Graphical overview of disaggregating a complex mapping unit using the catena method in S-World. S-World uses as a catena a toposequence, thus based on elevation. The toposequence is here from low to high, soil type C then A and as last B. Thus in complex mapping unit 1 the lowest 20% is disaggregated as B and the highest 80% as A. For complex mapping unit 2 this will result in the lowest 30% for B and the highest 70% for C. The result is that the complex mapping unit is disaggregated based on the distribution of the complex mapping unit and elevation into simple mapping units. Graphic from Stoorvogel et al. (2017).

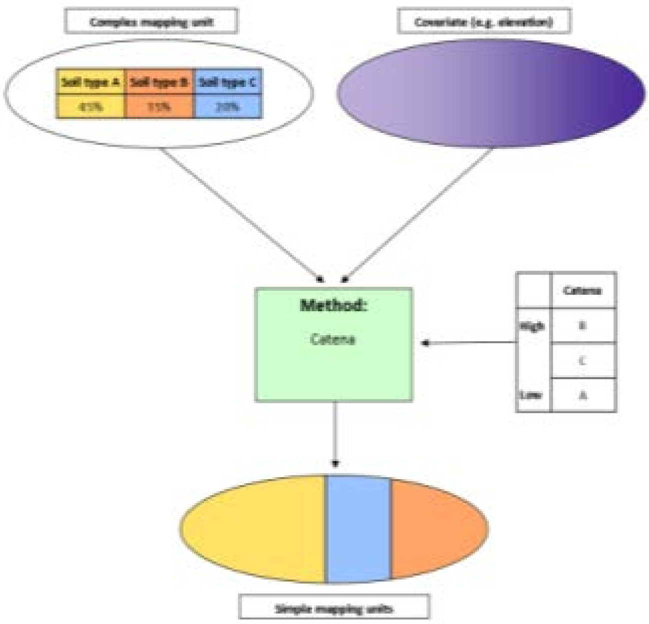

Figure 5 Schematic method of the catena method, where the disaggregation is based on one covariate, a catena and the distribution of the complex mapping unit.

An option to improve the disaggregation of complex mapping units is using multiple covariates. Relations between the covariates and the complex soil mapping will be used to disaggregate complex soil maps. However, these relations are not yet known. Therefore to relate soil properties to environmental properties, the *scorpan* formula of McBratney et al. (2003) is often used, but it is not explicitly defined. To approximate these relations machine learning, also known as statistical learning can be used. With machine learning, the relations are approximated in a training phase, where detailed soil maps will act as a known outcome of the disaggregation. The machine will then search for relations between the covariates and the detailed soil maps. The soil type distributions can be used in two ways, i.e. in the same way as the other covariates (the environmental covariates) or not as a covariate for the machine, but afterwards in combination with the probabilities of the machines.

Using machine learning to disaggregate complex mapping units is already done on smaller scales, e.g. Italy by Lorenzetti et al. (2015) and Häring et al. (2012) for Bavaria. However, both groups did the training of the machines in the same area as they planned to disaggregate and did not try to use machine outside the training area.

The goal of this study is to explore the use of machine learning with multiple covariates to disaggregate complex mapping units in soil maps and see if it is possible to use this method outside the areas used for the training.

Methods

Several methods exist to disaggregate or generalise complex mapping units into simple mapping units. These methods can be differentiated from each other by their use of covariates, if they use multiple covariates and how they handle the soil maps with complex mapping units (Figure 6). The dominant soil type method uses no covariates and the catena method uses one covariate. Disaggregating using multiple covariates can be done in two ways. The first method is to use the distributions of the soil types according to the complex mapping units as covariates for the machine just like the other environmental covariates. The other way is to only use the environmental covariates for the machine and then disaggregate at the level of the mapping unit using the probabilities according to the machine, while respecting the distribution of the complex mapping unit.

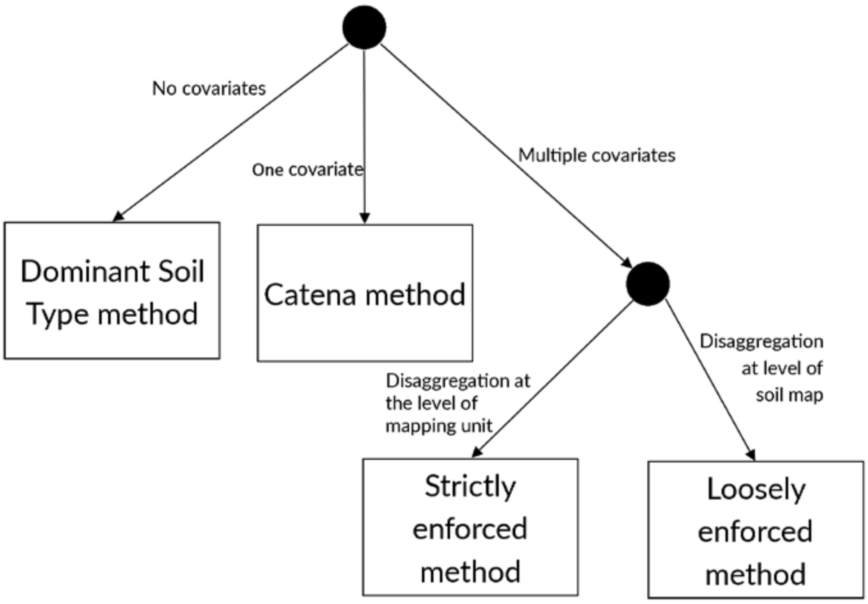

Figure 6 The four methods to convert complex mapping units into simple mapping units can first be differentiated based on their number of covariates they use. If no covariates are used, the method is called the dominant soil type method (DST). The catena method uses one covariate. When multiple covariates are used, the complex soil map can be used as a standard covariate, called the loosely enforced method and when it is not used as a standard covariate the strict enforced method.

To explore the application of multiple covariates to disaggregate complex soil maps, the loosely enforced and strict enforced method are further examined in this study. The methods were evaluated for two complex soil maps and use therefore two datasets. The first dataset is DA and uses STATSGO2 the other dataset is DB and uses the HWSD. The STATSGO2 covers United States at most places with a scale of 1 : 250.000. The HWSD has a global coverage at a resolution of 30 arc seconds.

As learning algorithm for the machines, two types of functions are chosen: multinomial logistic regression and tree ensemble. The multinomial logistic regression is done in R in much the same way as Kempen et al. (2009). However, for the machines using DA, 50 out the 128 soil were used as they covered the 95.55% of the training dataset. The other soil types were thus not taken into account, because they did not have enough records. In addition, the complex soil map was not taken into account. For DB multinomial logistic regression were not performed yet, due to the computational load. A tree ensemble is an adjusted random forest algorithm. The difference between a tree ensemble and a random forest is that with RF the trees use all the points. A tree ensemble uses instead for every tree only a randomly selected fraction of the training dataset. The logistic regression and tree ensemble were chosen because they differ a lot, in how they handle the training and because of their relative simplicity and flexibility. Other more advanced algorithms, like neural networks or support vector machines were also an option, but they cannot handle categorical variables and have a large computational load, making it not feasible for this study.

The disaggregation's in this study could thus differ in their disaggregation method (strictly of loosely enforced), which soil map (STATSGO2 or HWSD), and what type of machine (tree ensemble or multinomial logistic regression). An overview of the disaggregation models can be seen in Table 1.

Table 1 List of the disaggregation models and their characteristics

Name	Disaggregation technique	Algorithm	Dataset	Trainings points	Remarks
MLALR	Loosely enforced	Logistic Regression	DA	100 000	No complex soil map as input
MLATE	Loosely enforced	Tree Ensemble	DA	400 000	
MLBTE	Loosely enforced	Tree Ensemble	DB	1 000 000	
MSALR	Strict enforced	Logistic Regression	DA	100 000	
MSBTE	Strict enforced	Tree Ensemble	DB	1 000 000	
MSBLR	Strict enforced	Logistic Regression	DB	-	not completed

Loosely enforced disaggregation

The loosely enforced disaggregation treats the soil map with the complex mapping units the same as the other covariates. This means that the distributions of the soil types are used similar like the environmental covariates. This approach has some similarities with digital soil mapping. A function, i.e. the machine, which is based on empirical relations with the covariates, predicts a soil type classification. The function can have several forms and for this study, logistic regression and tree ensemble were chosen. The main difference with digital soil mapping is that with loosely enforced disaggregation no geostatistical techniques are used.

For dataset DA two machines were trained, one using a tree ensemble (MLATE) and the other one a logistic regression (MLALR). The MLATE was trained with the Konstanz Information Miner (KNIME) (Berthold et al. 2008) and uses 400 000 trainings points. The fraction of the data that every tree got, called the learning fraction, was set to 10%, the minimum node size, maximum tree depth was set to 20 and the number of tree at 100. These settings were chosen to reduce computational load and decrease the chance of overfitting, while still be able to achieve accurate results. The disaggregation is done by selecting the soil type that was predicted the most by the trees. The fraction of the trees predicting this soil type is called the confidence level and can be used as a proxy for the accuracy.

The MLALR was trained using the programming language R in much the same way as Kempen et al. (2009) using a multinomial logistic regression. The soil type that has the highest probability will be predicted as the disaggregated soil type for that location.

For the dataset DB a tree ensemble (MLBTE) was trained with 1 000 000 points. MLBTE has the same settings for the maximum tree depth, minimum node size, learning fraction and number of trees as for MLATE. In this way, they are very comparable, but use another dataset and different soil map to disaggregate.

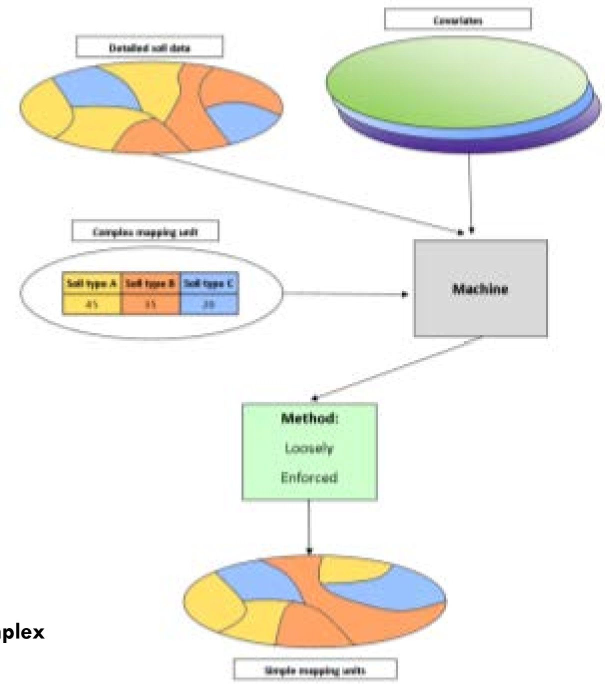

Figure 7 Schematic overview of the loosely enforce method, where a machine is trained with multiple covariates, detailed soil data and the complex mapping unit. The disaggregation is then based on the soil type with the highest probability according to the machine.

Strict enforced disaggregation

The strict enforced disaggregation method (Figure 7) uses the machines that only will be trained with the environmental covariates and the detailed soil data. When the disaggregation is done the machine will produce probabilities for every soil type that it will occur based on the input of environmental covariates. With these probabilities, an algorithm will be used that combines the probabilities and distribution according to the complex mapping unit to disaggregate the mapping unit into simple ones. In this way, the original distribution according to the complex soil map will be respected.

While the strict enforced disaggregation uses not the complex mapping units as a covariate for the machine, the machine settings are the same as for the machines for the loosely enforced disaggregation. This means that the MSALR is comparable with MLALR and MSBTE with MLBTE. MSBLR is similar to MLALR. In practice, the disaggregation is done at the level of the mapping unit, using the disaggregation algorithm and the calculated probabilities of the machine. With this information, the disaggregation algorithm will disaggregate the complex mapping unit in the following way:

- For the complex mapping unit the number of grid cells is counted.
- According to the distribution of the complex mapping unit, the rounded down amount of cells for soil types occurring in the unit is calculated by using the distribution fraction multiplied by the amount of cells in this complex mapping unit.
- Starting with the soil type that got the most cells in the complex mapping unit, the cells with the highest probability for this soil type according to the machine are assigned with this soil type.
- This continues with soil type with the second most cells in the mapping unit and then with next soil type until all soil types are done.
- Because of the rounding down of the amount of cells assigned, some cells are remaining. Those cells get the soil type that has the highest probability for that cell

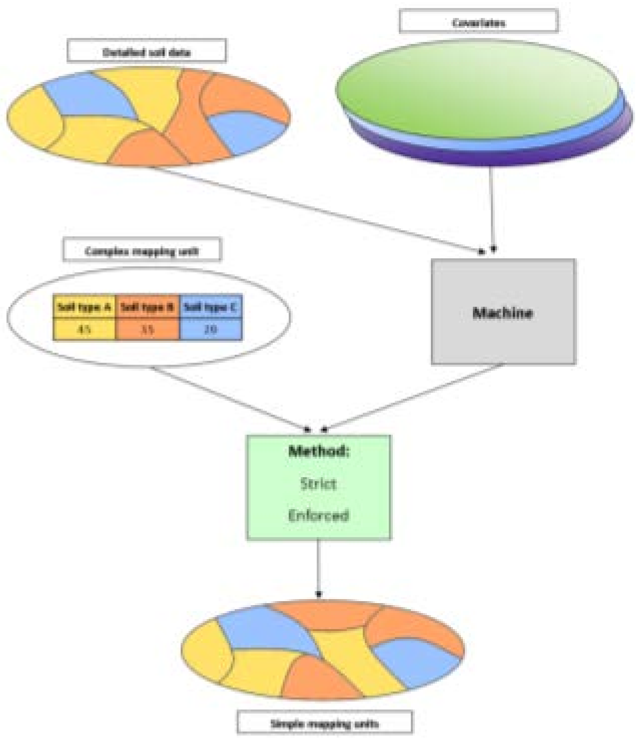

Figure 8 Schematic overview of the strict enforced method, where a machine is trained with multiple covariates and detailed soil data. The disaggregation is then based on the complex mapping unit and the probabilities calculated by the machine.

Soil data

To train the machine detailed soil datasets are needed to provide a “known” outcome of the disaggregation. With the “known” outcomes the machines can try to find links between the covariates and the detailed soil datasets. The detailed soil datasets are acquired from many different sources and from different regions around the world as can be seen in Table 2. These regions are called the training areas as there the training of the machine takes place. Due that, the detailed soil data was acquired from different sources their formats and classification system differed a lot. After they are pre-processed into the same format and classifications, the detailed soil datasets are combined into one dataset.

Table 2 Outline of the soil datasets used and their format, sources and soil classification system.

Type	Coverage	Dataset	Format	Classification System	Source
Complex	World	HWSD	Raster	WRB	Fao/Iiasa/Isric/Isscas/Jrc 2009
Complex	United States	STATSGO2	Polygon	Soil Taxonomy	Soil Survey Staff 2016b
Simple	United States	gSSURGO	Raster	Soil Taxonomy	Soil Survey Staff 2016a
Simple	Canada	National Soil Database	Polygon	Canadian	“National Soil Database,” n.d.
Simple	Brazil	Updated Brazilian’s Georeferenced Soil Database	Point	Brazilian	Muniz et al. 2011
Simple	New Zealand	FSL New Zealand Soil Classification	Polygon	New Zealand	“FSL New Zealand Soil Classification,” n.d.
Simple	Flanders	The soil map of the Flemish region	Polygon	WRB	Dondeyne et al. 2014
Simple	Costa Rica	Digital Soil Map of Costa Rica	Point	Soil Taxonomy	Mata Chinchilla and Sandoval Chacón 2016

First, the datasets require having the same classification system. This study will use the World Reference Base (WRB) as soil classification system (IUSS Working Group WRB 2015; IUSS Working Group WRB 2006). Therefore, datasets that use a different soil classification system were correlated using the correlation table in the Appendix. The correlation table was based on information from different sources (Krasilnikov et al. 2009; Soil Survey Staff 1999; Canarache, Vintila, and Munteau 2006; Soil Classification Working Group 1998; National Cooperative Soil Survey 2009). Every “foreign” soil type was correlated to 1 WRB soil type. This introduces an error, because soil types do not correlate exactly one to another. However, only one soil type could be used, which is the one that correlates the most. When the source uses older variations of the WRB, e.g. WRB2006 (IUSS Working Group WRB 2006), it was not correlated to the latest version, namely WRB2014 (IUSS Working Group WRB 2015). This was done to prevent even more correlation errors. The correlation table shows then the most likely soil type it could be correlated in WRB. However, around half of the listed soil types could be correlated in another way, by for example adding or removing a qualifier. Even another Reference Soil Group (RSG) could be possible, especially for soil types that correlate with the group Chernozems, Kastanozems and Phaeozems, the group Anthrosols and Technosols and the group Alisols and Acrisols.

After the correlation, the detailed soil data are converted to a point dataset. The advantage of converting to a point dataset is that apart from only soil maps, soil profile datasets also can be used. Soil profiles are actually verified in the field instead of interpreted by the soil mapper, nevertheless their support is limited and they contain less information than a soil map, because of their format. To convert the detailed soil data to points, the detailed soil datasets that were in polygon format were rasterized based on majority and with a 30 arc second mask. This mask ensures that all the soil data and covariates used in this research will have the same raster properties. The only raster dataset used, i.e. gSSURGO, was also resampled based on majority to the 30 arc second mask and added to the rasterized polygons. The combined raster dataset is then converted by replacing every cell by a point in the centre of the cell. Now the datasets with soil profiles can be added to the point dataset. In this way, a point dataset is created with detailed soil data from around the world (Figure 8).

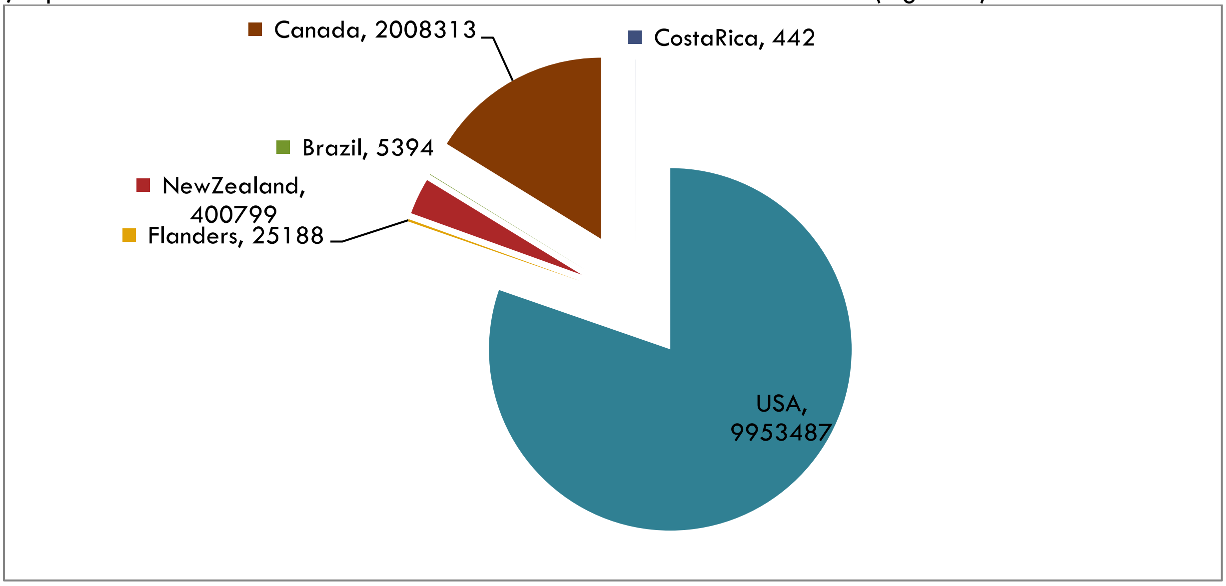

Figure 9 Amount of points per data source that are collected in total for all the datasets after the pre-processing is done.

The two complex soil datasets used in this study need also to have some pre-processing before usage. The STATSGO2 uses the Soil Taxonomy and has to be correlated to WRB using the correlation table in the Appendix. The format of the STATGO2 is polygon and is therefore rasterized to a 30 arc second raster by using the mapping unit that covers the largest part of the cell. The HWSD was already provided in WRB and in a 30 arc second raster and needs no correlation and resampling. However, for both complex soil maps the distribution of the soil types was reduced to the level of RSG in order to reduce the dataset size. The information of the complex soil data were added to points generated with the detailed soil data.

Two datasets were created with a selection of the points, as using all the points would be infeasible. Dataset DA contains 20% of the points located in 20 US states with the detailed soil data from the gSSURGO. The other dataset (DB) holds 1 307 494 points randomly selected from all the datasets used. The distribution of the points in DB can be seen in Figure 9. Costa Rica and especially Brazil have a very low percentage of the points in DB, because only soil profiles were available, which generate fewer records than soil maps. However, they are located in (climatic/pedological) regions that would not be covered by the other datasets and are verified in the field. Most of the detailed soil data are from the USA with almost ten million points located at the United States, its unincorporated territories and associated states. This is by the huge coverage of the gSSURGO, which genereates many records in the point dataset. To reduce the risk of biasing the machine, only 7% of the points in the USA are selected. For Flanders 80% was selected, a rather high value was selected as it was the only detailed soil dataset that did not have to be correlated. However, still the majority of the points in DB were located in the USA.

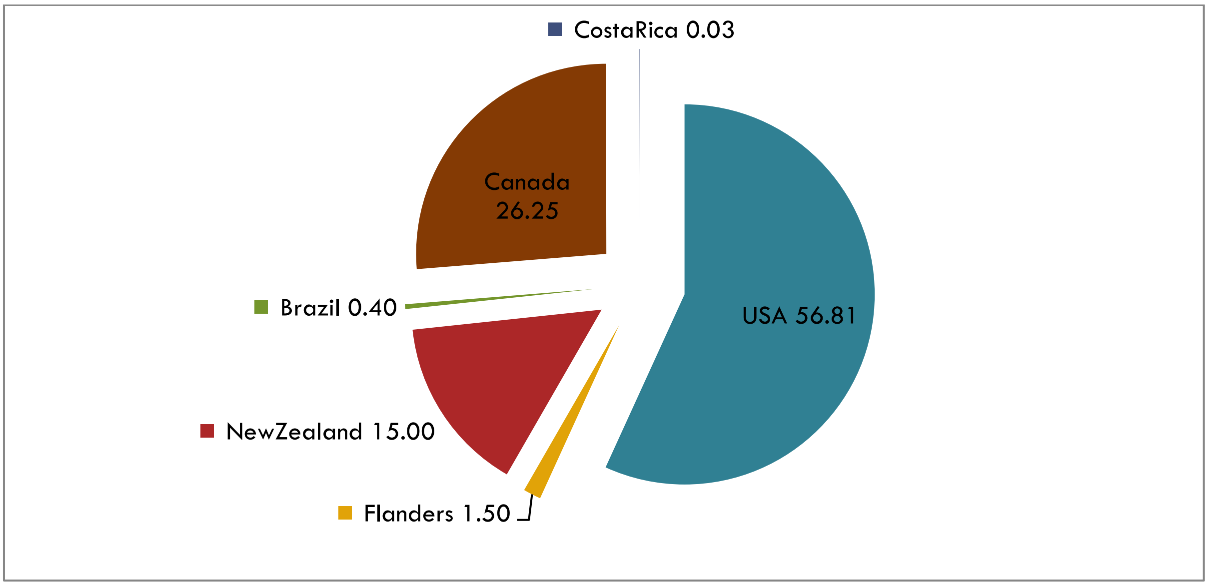

Figure 10 The percentage of points per data source for dataset DB.

Covariates

Seventeen environmental properties were selected as covariates to resemble the *scorpan* factors. There were no covariates selected to resemble the age and spatial position. For the reason that there are no datasets available for soil age. The spatial position is not used as it is already incorporated in the other factors, like this is done by the *corpt* formula of Jenny (1941).

The soil component factor in the scorpan formula is treated differently than the other factors. This factor is resembled by the distributions of soil types in the complex mapping unit. This is prior soil information that loosely enforced disaggregation will use in the same way as the environmental covariates. The strict enforced disaggregation will not use the distribution of soil types as covariate for the machine, but uses the distributions when the disaggregation algorithm is used.

The climate factor is resembled by eight numeric covariates that cover different aspects of temperature and precipitation. Mainly their mean values are used and how they vary per year, season and day. This data was acquired from the bioclimatic variables from WorldClim at a 30 arc second resolution (Hijmans et al. 2005).

The organism or vegetation factor is assumed to be correlating with the NDVI. The NDVI is often used as a source to estimate biomass or plant activity (Glenn et al. 2008). The dataset is acquired from the ESA Climate Change Initiative - Land Cover project 2014-2017. This dataset consists out 52 images with the average NDVI for every week in the years 1999 until 2012. The mean of the 52 images was calculated and bilinear resampled from 1 kilometre grid to 30 arc second.

For the relief factor, six numerical DEM derivatives were calculated and one categorical dataset was used. The numerical topographic covariates were derived from the GMTED2010 (Danielson and Gesch 2011) and calculated with the Geomorphometry and Gradient Metrics Toolbox (Evans, Cushman, and Theobald 2014). Especially the Compound Topographic Index (CTI) and landform curvature seem to be important as they correlate with soil depth and other soil characteristics (Gessler et al. 1995). The landform type is from the Sayre et al. (2014) and they characterised the whole world in 10 types of landform based on a landform classification of Hammond (1954) and the GMTED2010.

Sayre et al. (2014) published also a lithology map with 16 types of lithology, which will serve as the covariate that approximates the factor parent material. Their source was the GLiM developed by Hartmann and Moosdorf (2012).

Table 3 The *scorpan* factors used and by which covariates they are approximated and their source

<table>
<tr><th>Factor</th><th>Covariate</th><th>Source</th></tr>
<tr><td rowspan="7">Relief</td><td>Compound Topographic Index</td><td rowspan="6">Danielson and Gesch (2011); Evans, Cushman, and Theobald (2014)</td></tr>
<tr><td>Dissection</td></tr>
<tr><td>Heat Load Index</td></tr>
<tr><td>Landform Curvature</td></tr>
<tr><td>Roughness</td></tr>
<tr><td>Surface Area Ratio</td></tr>
<tr><td>Landform type</td><td rowspan="2">Sayre et al. (2014)</td></tr>
<tr><td>Parent material</td><td>Lithology type</td></tr>
<tr><td rowspan="8">Climate</td><td>Isothermality</td><td rowspan="8">Hijmans et al. (2005)</td></tr>
<tr><td>Maximum Temperature Warmest Month</td></tr>
<tr><td>Minimum Temperature Coldest Month</td></tr>
<tr><td>Mean Diurnal Range</td></tr>
<tr><td>Temperature Seasonality</td></tr>
<tr><td>Annual Mean Temperature</td></tr>
<tr><td>Precipitation Seasonality</td></tr>
<tr><td>Annual Precipitation</td></tr>
<tr><td>Organism</td><td>Mean NDVI</td><td>ESA Climate Change Initiative - Land Cover project 2014-2017</td></tr>
</table>

At the end of the pre-processing of the data, the datasets contain the soil type according to the detailed soil data, the distribution of the RSG's by the complex soil maps and the covariates and are ready to be used.

Validation

Both datasets were split in a trainings set and a validation set (Table 4). The validation points were randomly selected and left out of the training process. The validation datasets are thus located in the training areas. To examine the disaggregation models when they disaggregate outside the trainings areas, the datasets are created with covariates and information from the complex mapping units. For dataset DA, Kansas was available to assess the accuracy of the machines when disaggregating outside the training areas. However, for dataset DB, there was no detailed soil data available outside the trainings areas and only the confidence levels of the machines using the tree ensemble could be used.

Table 4 Comparison between the datasets DA and DB, in the number of points that could be maximum used for training and validation and which soil map with complex mapping units is used.

	DA	DB
Complex soil map	STATSGO2	HWSD
Training (max)	705 329	1 000 000
Validation	40 000	305 117
Left out	1 180	2 377
Total	746 509	1 307 494

Results

The disaggregation methods were evaluated based on their accuracy for the validation datasets (Figure 11). For the strict enforced method, the accuracy is estimated by using the most probable soil type and thus the disaggregation algorithm is not used here. The curves show a logarithmic trend with the increase of the amount of trainings points, which means that there is a theoretical maximum of the accuracy than can be achieved.

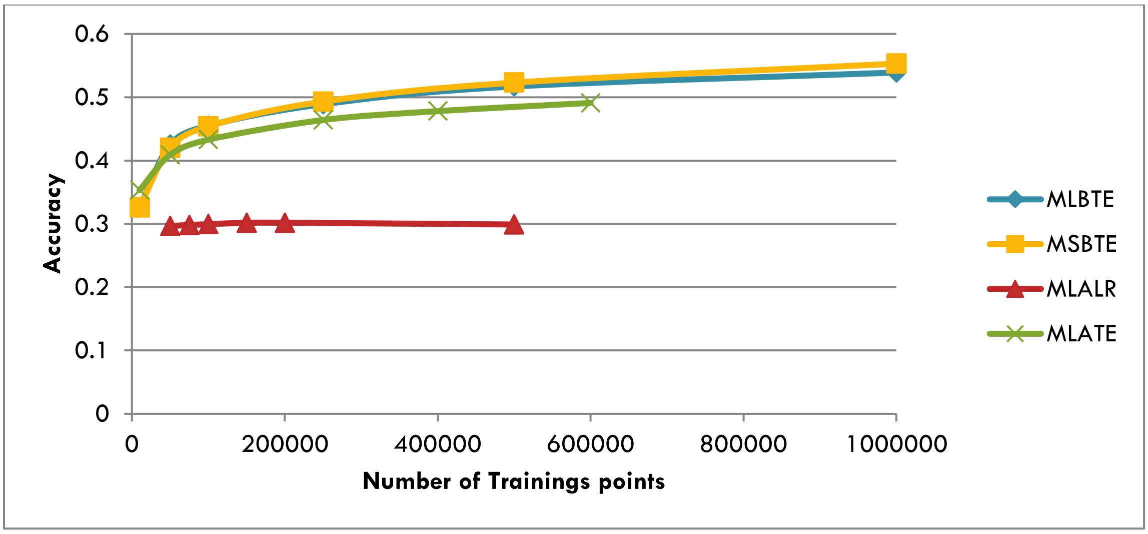

Figure 11 The accuracy of the machines compared with the number of trainings points. Except for MLALR, all the machines seem to follow a logarithmic trend and thus will always have a theoretical maximum accuracy they could achieve.

To evaluate the different configuration options for machines using the tree ensemble algorithm, 20 variations of MLATE with different configurations were trained. The options that were evaluated were the amount trainings of trainings points (n), the maximum tree depth (T_d) and the minimum node size (L_s). A logarithmic regression model was fitted to data and could approximate the accuracy with a R^2 of 0.9995.

$$Accuracy = 0.0375\ln(n) + 0.0269\ln(T_d) - 0.0287\ln(L_s)$$

```
Call:
lm(formula = Prediction_test ~ 0 + Ln.n. + Ln.Ts. + Ln.Ls., data = tree_ensemble)

Residuals:
Min          1Q      Median         3Q         Max
-0.0170294 -0.0071663  0.0002841  0.0088910  0.0108630

Coefficients:
Estimate Std. Error t value Pr(>|t|)
Ln.n.   0.037503   0.001589  23.606 1.96e-14 ***
Ln.Ts.  0.026864   0.004870   5.517 3.77e-05 ***
Ln.Ls. -0.028714   0.002158 -13.308 2.04e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.009148 on 17 degrees of freedom
Multiple R-squared:  0.9996,       Adjusted R-squared:  0.9995
F-statistic: 1.373e+04 on 3 and 17 DF,  p-value: < 2.2e-16
```

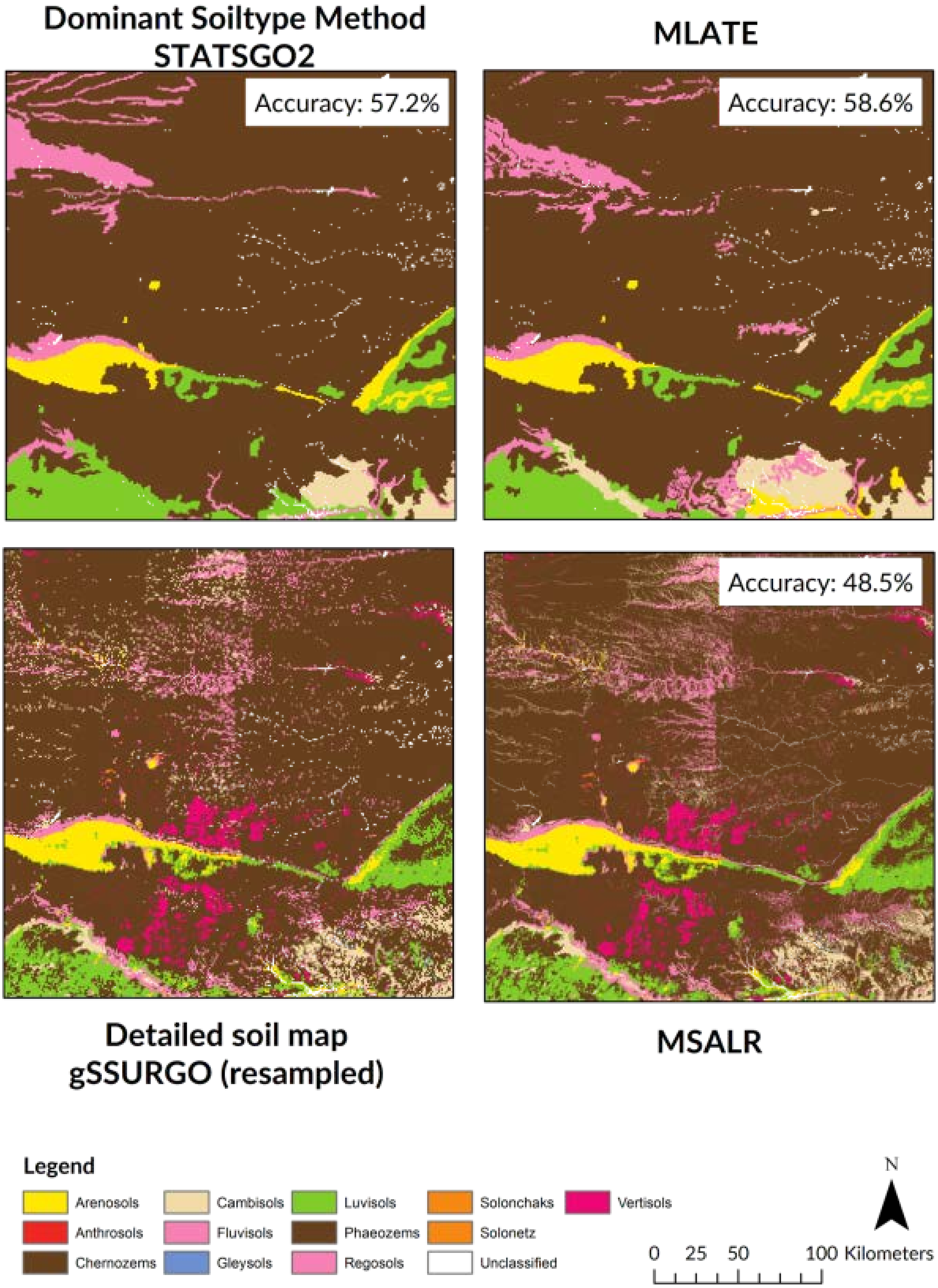

Figure 12 Close up of South West Kansas converted from the complex mapping units in STATSGO2 to simple map units, using DST, MLATE and MSALR. Kansas was not included in the training dataset DA and as comparison the detailed soil map is provided.

For dataset DA the validation area was Kansas, thus was not included in the training at all. Figure 12 shows the results of the three different disaggregation methods for South West Kansas. The MLATE, MSALR and the dominant soil type method were compared with the detailed soil map (gSSURGO) of the area. Differences between the maps can be noticed immediately and the first thing that stands out is that MLATE and DST ignore the Vertisols completely, although there are some large patches of Vertisols according to the gSSURGO. However, MSALR predicts very small patches of Vertisols, but not at the correct place. Another noticeable thing is the strip in the south where MLATE outlines Cambisols; the dominant soil type method expects to be Luvisols and MSALR Fluvisols with Cambisols or Luvisols. Also east of this strip some differences are noticeable. There the DSM predicts close to the river Fluvisols followed by Calcic Chernozems and Luvic Phaeozems, while the MLATE expects a catena starting at the river with Phaeozems, then Regosols and Luvic Phaeozems. The MSALR predicts Fluvisols, followed by Luvisols and then Luvic Phaeozems. Looking at the detailed gSSURGO, the toposequence is as follows: Fluvisols at the riverside, surrounded by (Gleyic) Phaeozems, then Regosols with some patches of Cambisols and Luvic Phaeozems at the top of the toposequence.

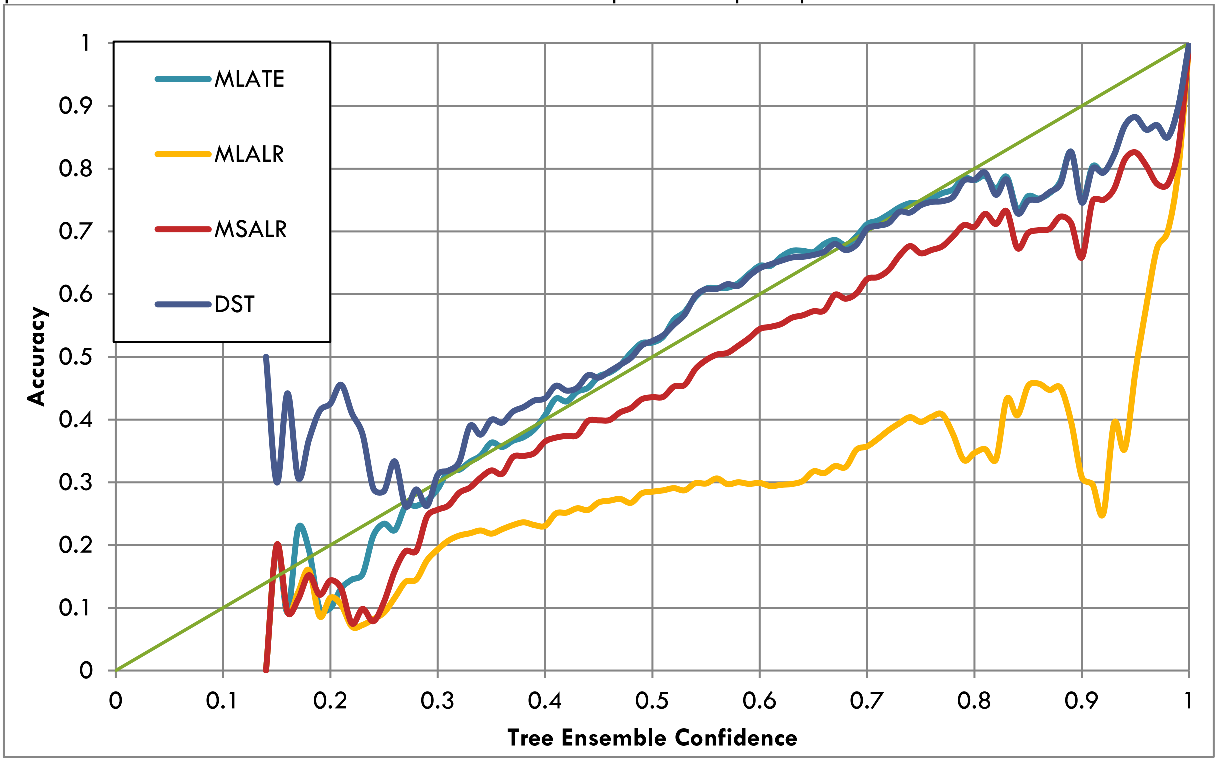

Figure 13 The accuracy of the different machines for Kansas using the dataset DA plotted against the confidence level of MLATE. Most of the data lies between the 0.3 and 0.8 of the confidence level. If the machines follow the 1:1 line, the confidence level will be a good proxy for the accuracy.

When the accuracy is calculated for the whole of Kansas and plotted against the confidence level of MLATE, it can be seen that the MLATE follows the 1:1 line mainly in the part where a large majority of the cells is present, the range from 0.3 until 0.8. It shows also that MLATE performs almost the same as the dominant soil type method, but it must be noticed that the DST does not use the variation in the map units while MLATE and certainly MSALR does include. It shows also that the disaggregation algorithm significantly improves the disaggregation compared when only the most probable soil type is used.

With the machines trained for dataset DB, Northern Europe was selected to extrapolate. The MSBTE used only the most probable soil type and did not use the disaggregation algorithm, as it was too computational heavy. The MLBTE has more variation than MSBTE; probably due it incorporated the HWSD. The accuracy could not be assessed, as only for Flanders, there were detailed soil maps available, but they were used in the training. To approximate the accuracy, the confidence level can be used, which is for MSBTE 0.26 and for MLBTE 0.20. This is very low and means that the disaggregation of Northern Europe is done with a large error and probably DST would deliver a better job. For the disaggregation in Figure 14, it can be seen that the confidence levels are much higher in the USA and Canada, than in Mexico and the other countries. As there were no trainings points located in the other countries this was expectable.

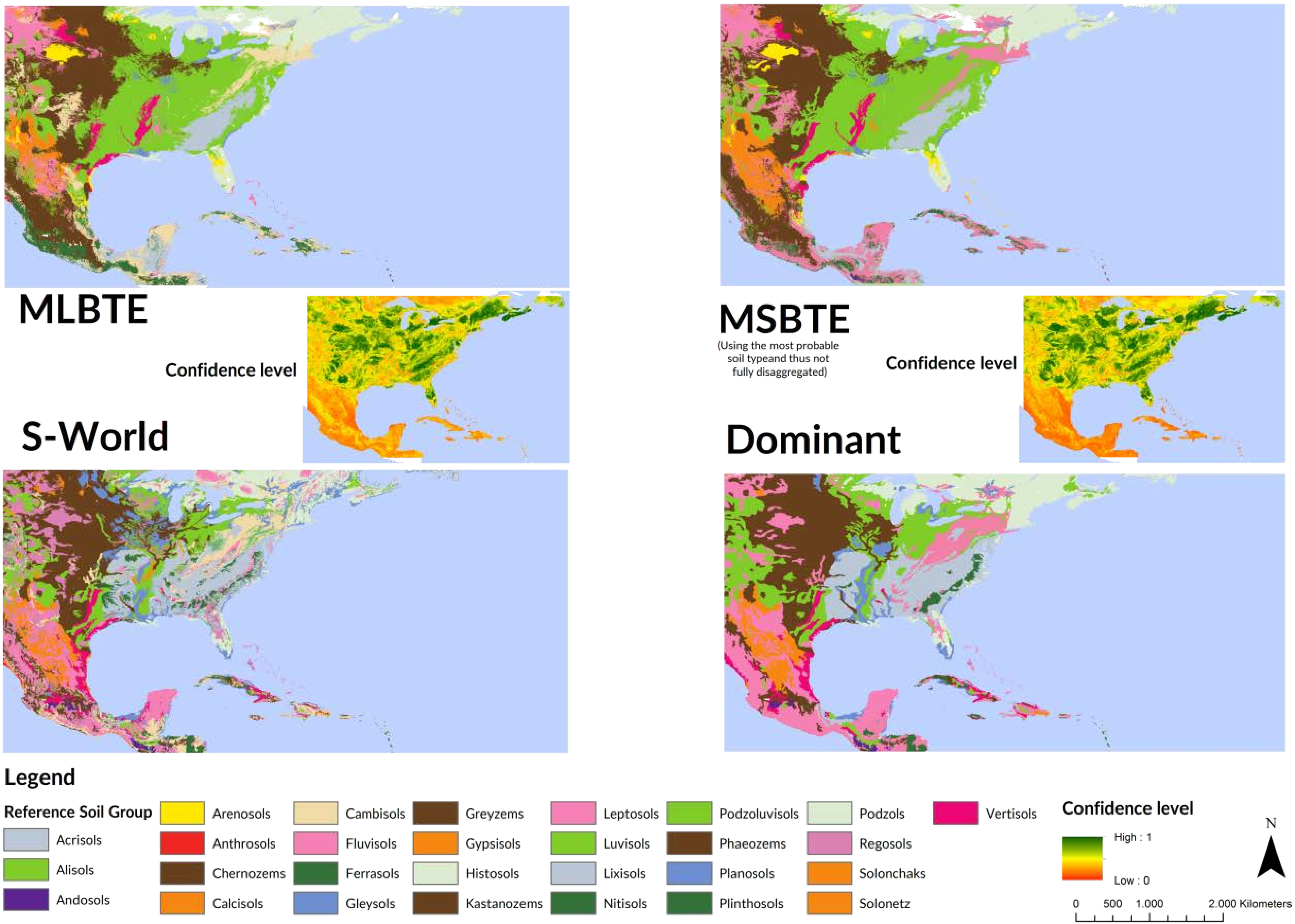

Figure 14 The results of the disaggregation of the machine MLBTE and MSBTE compared with S-World and the DST method. For all the maps, the soil types are reduced to the level of RSG. In addition, the confidence levels of the machines are plotted and a clear distinction can be seen between the confidence level in areas where the training took place (USA and parts of Canada) and where no data is used for the training (Mexico and the Caribbean).

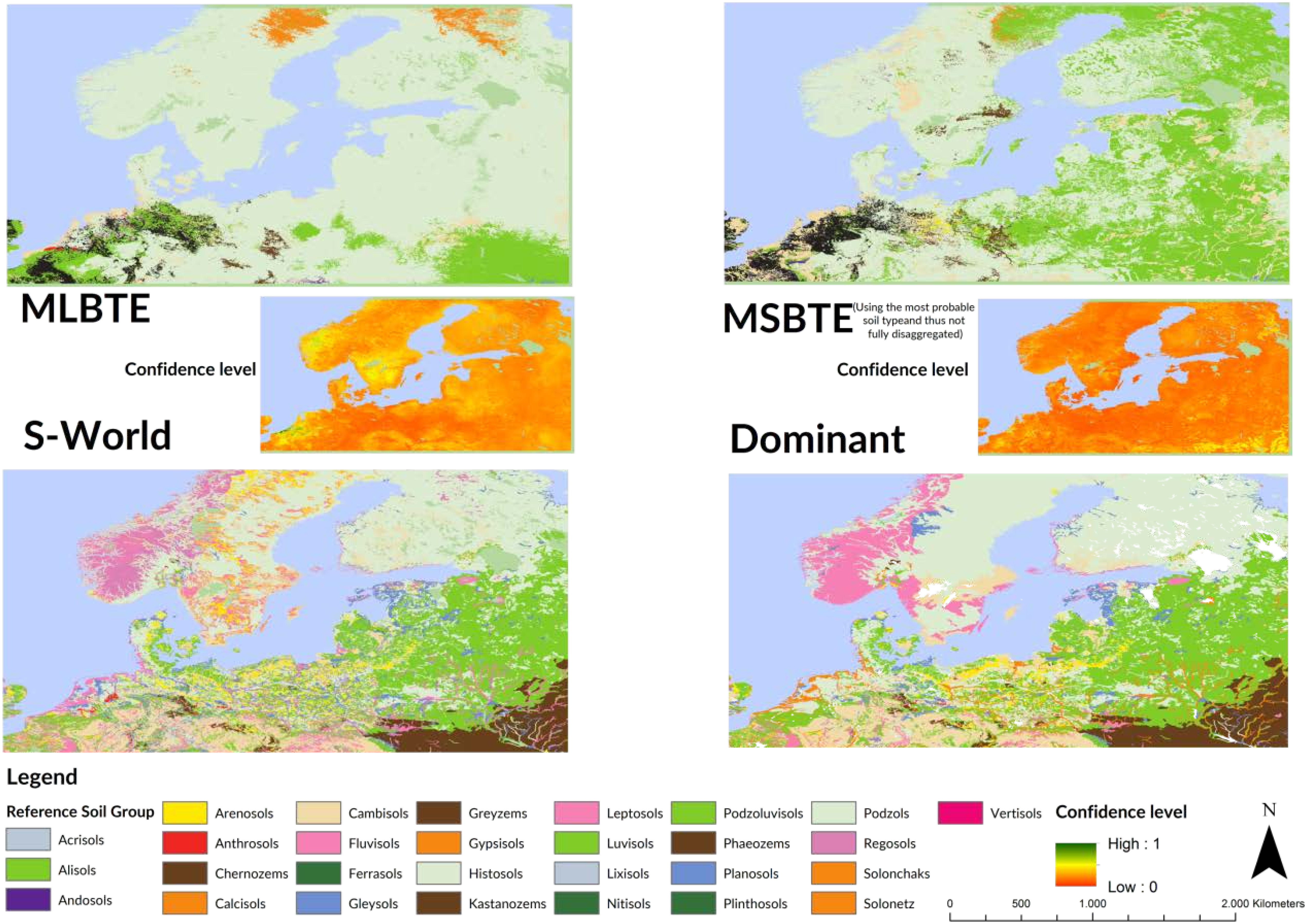

Figure 15 The results of the disaggregation of the machine MLBTE and MSBTE compared with S-World and the DST method. For all the maps, the soil types are reduced to the level of RSG. The confidence level is also plotted with an average value of 0.26 for MLBTE and 0.20 for MSBTE.

Discussion

Developing the disaggregation methods

One of the main problems is how to assess the methods. In this study the accuracy is used, by giving a 1 for an exact correct prediction and otherwise a 0. The average of all those ones and zero gives the accuracy. However, making such as sharp boundary between a correct prediction and an incorrect prediction is arguable. For example when the Reference Soil Group is predicted correctly, but not the qualifier, the disaggregation model came close. Another example is a disaggregation model predicting a RSG that is closely related, e.g. Chernozems vs Kastanozems, compared with a disaggregation model that predicts a very different RSG, e.g. Chernozems vs Histosols. In this study, the accuracy is estimated by only using the exact correct predictions. This results that in the examples mentioned before, all predictions were classified as wrong, nevertheless intuitively, some of the disaggregations feel to perform better than the other ones. Another aspect is the disaggregation model compared with a human soil surveyor in the field. Some qualifiers are based on variables, e.g. base saturation, and are needed to be measured in a laboratory. Only then, the qualifier Eutric or Dystric can be assigned to the soil description, but it is not possible to do this easily at the soil pit. It is then questionable if the machine should perform just as well compared with more easily to measure qualifiers.

A solution to these accuracy problems could be to not only use 1 for exactly correct and 0 for the other predictions, but also values in between. Rossiter et al. (2017) propose to use the taxonomic distance as the value to assess the accuracy. A short taxonomic distance would result to value close to 1 and a long taxonomic distance to a value of 0. A table with taxonomic distances does not exist yet and has to be calculated by ourselves. To calculate the taxonomic distance Rossiter et al. (2017) use the square root of the divided amount of present diagnostic and environmental conditions for soil type A by the amount of present conditions for soil type B. However, choosing which conditions and when they are present is a subjective choice. Also when the data used to calculate the taxonomic distance is the same as is used for the training and validation of the disaggregation model, the taxonomic could be biased, which results serious problems when extrapolating. The table with taxonomic distances would also be huge as for example MLBTE could choose out of 330 soil type, leading to a table of 108 900 values. Instead of calculating the taxonomic distances, using the presence of diagnostic and environmental conditions the hierarchal system of soil classification could be used. This leads to the problem that the WRB does not have a clear hierarchal structure and some soil types may be more correlated than they are according to the structure of the system (Krasilnikov et al. 2009).

Using a validation dataset gives quite a good understanding of the quality of the disaggregation model. This data is not used for the training, but is located in the training area. However, for the strict enforced method it cannot be used, as it is a random selection of points and not whole mapping units. Therefore, the disaggregation algorithm cannot be applied on the validation dataset and only the most probable soil type can be used. To estimate the accuracy of the strict enforced method a whole area is needed, that has a detailed soil map and thus will be left out of the training. For DA Kansas was chosen to be the validation area. The disadvantage of this that only the accuracy is measured for that particular area with its combination of covariates for that landscape and climate. This is maybe the reason that the loosely enforced machine MLATE got a higher accuracy for Kansas than it has for the standard validation dataset. So validating in this way is very hard and difficult to interpret and will probably need more areas to be left out of training which results in a smaller trainings dataset, but it is the only way of validating the strict enforced method.

Another aspect of the accuracy and more difficult to measure is the quality of the disaggregation spatially. When the complex mapping unit is disaggregated into zones with only simple mapping units, it is important that it follow the contours that occur in the real world. With the accuracy as calculated as above, this is not captured, as this only takes correct if it is on the right spot and not the shape. To measure this it has same the problem as the validation of the strict enforced method. It is not possible to use the validation set as it covers a random selection of points and not mapping units. Thus, an area is needed to validate. The soil type would then be neglected and the shapes of the new simple map units would then be compared with the real world. However, this would require quite a difficult algorithm to calculate the similarity.

Besides evaluating the disaggregation methods on their accuracies, the quality of the data used as input is also important to achieve reliable results. The data that are used can be divided in the detailed soil data, the complex soil data and the covariates. The qualities of the detailed soil data are very important for the training of the machines, as it will be assumed the truth. However, as a rule of thumb, 70% of a soil map is correct. This results that 30% of the trainings dataset and validation dataset is incorrect, while it is used as the truth. This may be to a lesser extent for the soil data from profile datasets as they are verified in the field by a soil surveyor, but also there errors could occur. It should therefore be kept in mind that the disaggregation models do not disaggregate the real world, but the world according to the soil maps. For the loosely enforced method, it is very important that there are meaningful relations between the complex soil map and the detailed soil data. Otherwise, when the difference in scale between the complex soil maps and detailed soil data is too large, it would be worthless to search for relations. This could have happen for MLBTE in North America, where the HWSD does not have a large degree of detail, while there are very detailed soil maps for the USA and Canada. This happened, because North America in the HWSD was not updated anymore after the completion of The Soil Map of the World in 1960 (Fao/Iiasa/Isric/Isscas/Jrc 2009). For the disaggregation models using DA, this is solved by using the STATSGO2, which seems to be more related to the detailed soil data than the HWSD. This problem is not a big issue for the strict enforced method, as it does not search for relations with the soil type distribution in in the trainings phase. However, it will use the information from the complex mapping units in the disaggregation algorithm, so the disaggregated results will have the same scale and detail level as the soil map with complex mapping units.

For the covariates, the main problem is which variables are chosen to resemble the *scorpan* factors. There is no standard way of doing this so it will always be a more or less subjective choice if the covariates resemble the *scorpan* factors. Besides this, there are two other requirements for the covariates. First, they should be globally available, which ensures that if relations are found they can be used everywhere to extrapolate. Second is that they have at least the same detail level as the complex soil map, in this way the covariates can have the same resolution as the soil map with complex mapping units. To see whether the covariates encapsulate the real world the density distribution of the covariates in the trainings dataset and the real world could be overlaid to see what kind of areas are over- or underrepresented. Using the overlay the machine can be inspected if it will be possible biased to some regions, which could lead to curious disaggregation results. The amount of covariates is also a subjective choice. Too few variables and differences between soil regions could not be seen, but too many will result in hard to find relationships and a large computational load. Thus, the covariates should be selected on their interaction with the soil forming processes.

Comparing disaggregation methods

When comparing the outcomes of the disaggregation models they can be very different. This is the result of the very diverse ways of disaggregating the complex mapping units and there is not one single method that is the ideal way of doing the disaggregation. The advantage of using the dominant soil type method is that it is the quickest and easiest way to convert the complex soil map in a soil map with simple units. There are no covariates and no detailed soil maps needed or difficult algorithms. Nevertheless, you lose all the variation in the complex mapping unit as you assign the whole mapping unit to one soil type. This is not a problem if the soil type is very dominant, but there are many places where this is not the case and introduces a large error. However, the error is easy to estimate, as it is equal to the fraction of the other soil types, when the complex soil map would be completely right.

The catena option has the advantage that it keeps the original variation of soil types in the complex mapping unit and it is easy to understand the disaggregation process. The disadvantage of the catena method is that soil cannot be explained using one covariate and therefore very difficult to choose the covariate. In addition, the ranking in the standardized sequence is based on expert knowledge and it is questionable if soils keep themselves to the catena in all the different circumstances of the world.

Using more covariates would supposedly be better. However, there is no fixed formula for the relations between soil types and their environments. The loosely enforced method got high accuracy results in the areas where it was trained or that have more or less the same landscapes and was easy to validate when leaving points out of the training. However, extrapolating is quite tricky as the accuracy drops and it does not keeps itself to the distribution of soil types according to the complex soil map. This can lead to strange disaggregation results and it is very difficult to trace back why the disaggregation is done in that way.

The strict enforced method has fewer problems with extrapolating the disaggregation model, because it keeps itself to the distribution according to the complex mapping unit. This leads to a more pedological sound way of disaggregating soil maps with complex mapping units. The disadvantage of this method is that after predicting the probabilities, they have to be noted for every soil type alongside with the distributions of the occurring soil types according to the complex mapping units. This creates a huge dataset and the disaggregation algorithm will take a large computational load if not programmed efficiently. Another obstacle occurs when a soil type is not covered in the trainings dataset but occurs in an area that will be disaggregated; those areas will then get the soil type with the highest probability and the disaggregation would differ a little bit compared with the original distribution.

Conclusions

Disaggregating complex mapping units in soil maps can thus be done in several ways. The ideal option seems to be he strict enforced method theoretically, but has the disadvantage that it is difficult to process the algorithm and cannot be easily validated. This can be solved by using the loosely enforced method, which can be validated and processed more easily. However, this study shows that when disaggregating outside the training areas some curious results can happen and should be carefully done. These results are possible due that the disaggregation model is possibly biased to the training areas and does respect the distribution of the complex soil map, which leads to different results compared with the distribution of the complex soil map. For the algorithms used to learn the machines, the machines seem perform better with a tree ensemble than with multinomial logistic regression. The tree ensemble can handle more trainings points, has lower computational load and achieves higher accuracies than the multinomial logistic regression. When in the future the large soil maps with complex mapping units, e.g. HWSD, would be disaggregated, the MSBTE would be the best option. Nevertheless, the MSBTE has to be improved by using a larger variation of trainings points from around the world, having a more efficiently programmed disaggregation algorithm, and more sophisticated computing and better way to assess the accuracy of the disaggregation results. When this would be achieved, soil data would be better accessible to a public outside the field of soil science, leading to a better understanding of soils and their values.

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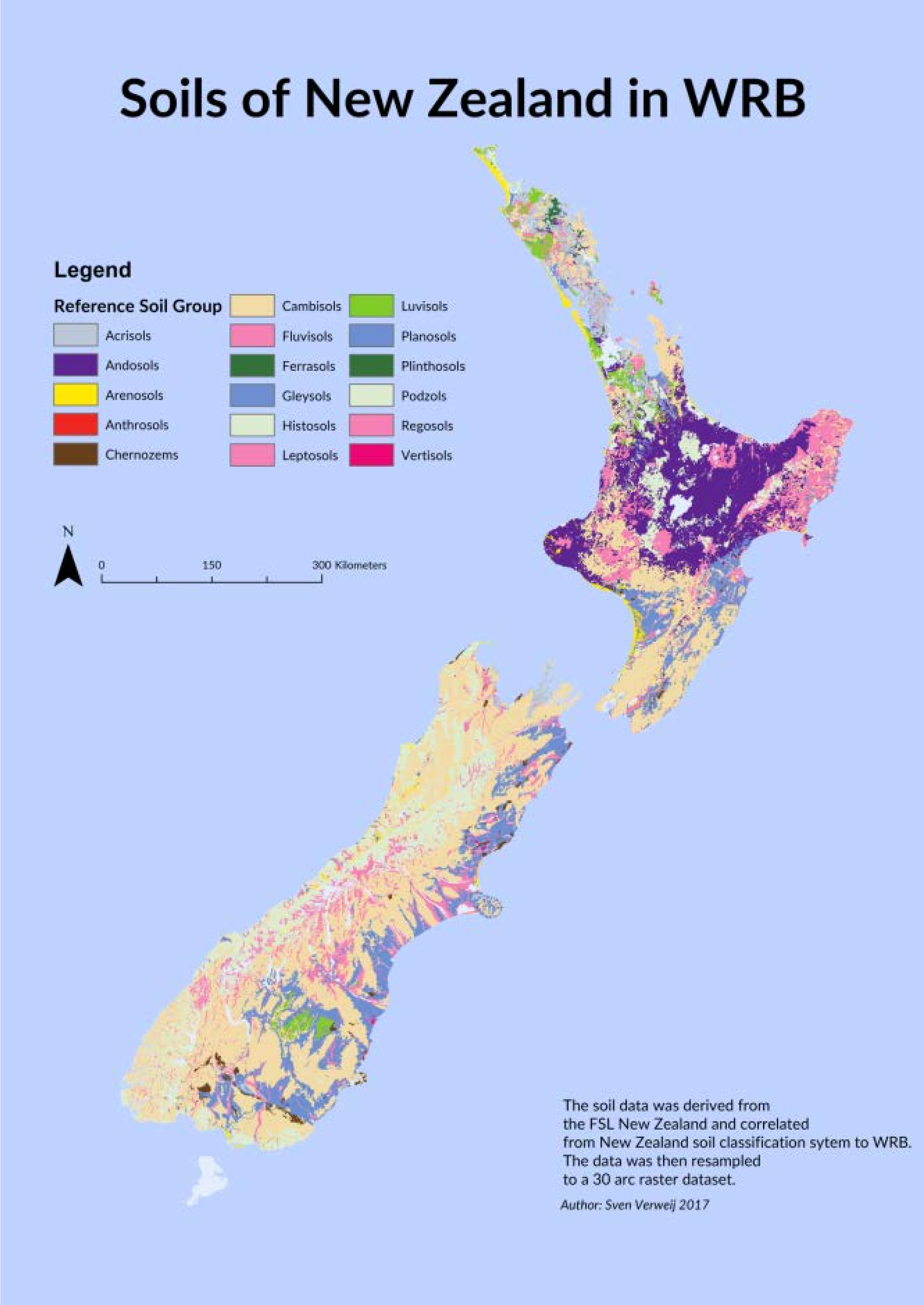
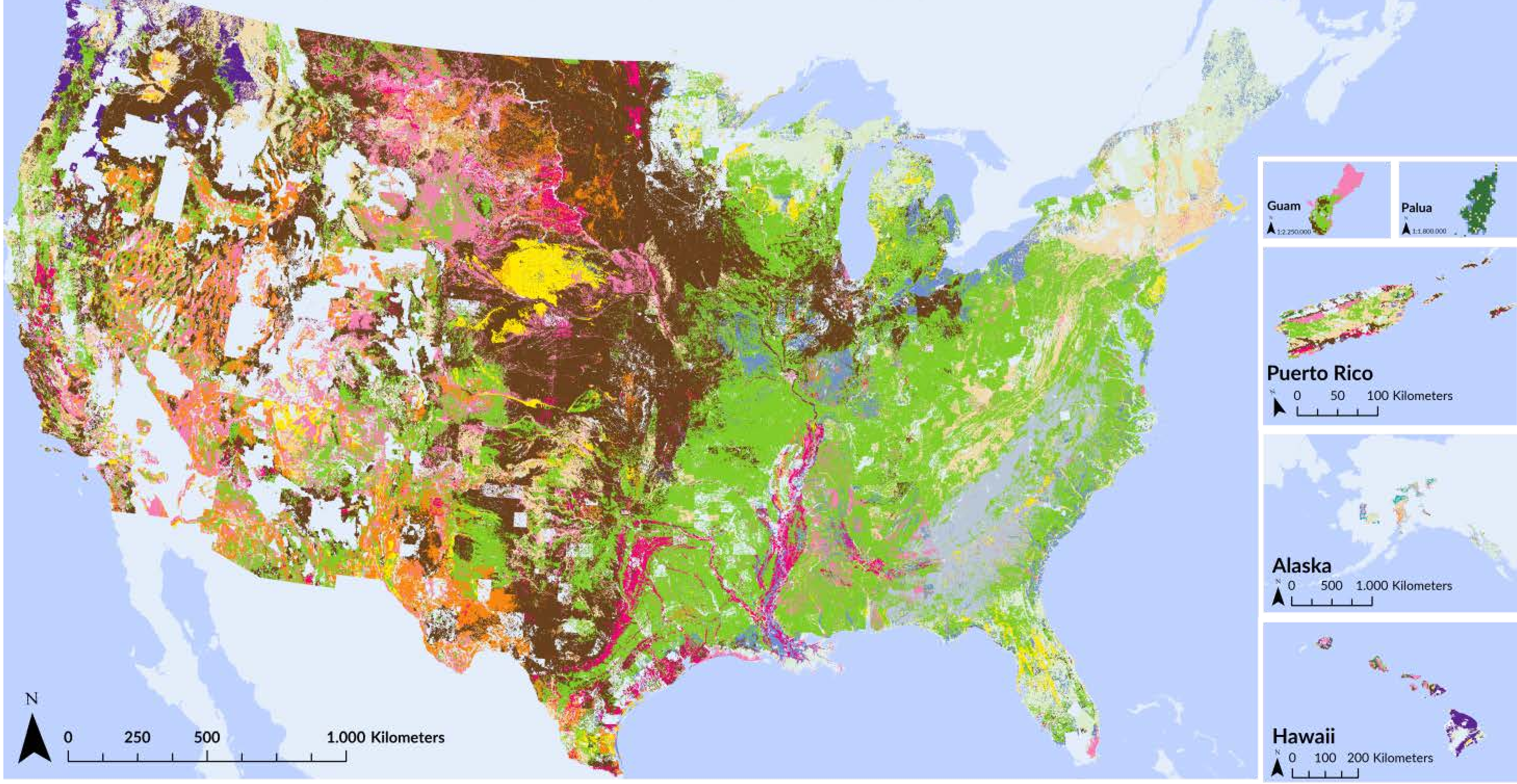

Soils of New Zealand in WRB
Legend
Reference Soil Group
Acrisols
Andosols
Arenosols
Anthrosols
Chernozems
Cambisols
Fluvisols
Ferrasols
Gleysols
Histosols
Leptosols
Luvisols
Planosols
Plinthosols
Podzols
Regosols
Vertisols
N
0
150
300 Kilometers
The soil data was derived from
the FSL New Zealand and correlated
from New Zealand soil classification sytem to WRB.
The data was then resampled
to a 30 arc raster dataset.
Author: Sven Verweij 2017

Soils of the United States in WRB



Legend

Reference Soil Group

Albeluvisols	Andosols	Calcisols	Fluvisols	Histosols	Lixisols	Regosols	Umbrisols
Acrisols	Arenosols	Cambisols	Ferrasols	Kastanozems	Phaeozems	Solonchaks	Vertisols
Alisols	Anthrosols	Cryosols	Gleysols	Leptosols	Planosols	Solonetz	
	Chernozerms	Durisols	Gypsisols	Luvisols	Podzols	Stagnosols	

The soil data was derived from the gSSURGO and correlated from Soil Taxonomy to WRB. The data was then resampled to a 30 arc raster dataset.

Author: Sven Verweij 2017

Soil Correlation table

Classification system	Level 1	Level 2	Level 3	WRB name	WRB code
Brazil	Alissolos	Alissolos Crómicos	AlissolosCrômicosargilúvicos	Cutanic Alisols	ALct
Brazil	Alissolos	Alissolos Crómicos	AlissolosCrômicoshúmicos	Alisols	AL
Brazil	Alissolos	Alissolos Crómicos	AlissolosCrômicosórticos	Alisols	AL
Brazil	Alissolos	Alissolos Hipocrômicos	AlissolosHipocrômicosargilúvicos	Cutanic Alisols	ALct
Brazil	Alissolos	Alissolos Hipocrômicos	AlissolosHipocrômicosórticos	Alisols	AL
Brazil	Argissolos	Argissolos Acinzentados	ArgissolosAcinzentadosdistróficos	Acrisols	AC
Brazil	Argissolos	Argissolos Acinzentados	ArgissolosAcinzentadoseutróficos	Lixisols	LX
Brazil	Argissolos	Argissolos Amarelos	ArgissolosAmarelosdistróficos	Acrisols	AC
Brazil	Argissolos	Argissolos Amarelos	ArgissolosAmareloseutróficos	Lixisols	LX
Brazil	Argissolos	Argissolos Vermelho-Amarelos	ArgissolosVermelho-Amarelosalumínicos	Acrisols	AC
Brazil	Argissolos	Argissolos Vermelho-Amarelos	ArgissolosVermelho-Amarelosdistróficos	Acrisols	AC
Brazil	Argissolos	Argissolos Vermelho-Amarelos	ArgissolosVermelho-Amareloseutróficos	Lixisols	LX
Brazil	Argissolos	Argissolos Vermelhos	ArgissolosVermelhosditróficos	Acrisols	AC
Brazil	Argissolos	Argissolos Vermelhos	ArgissolosVermelhoseutroférricos	Acrisols	AC
Brazil	Argissolos	Argissolos Vermelhos	ArgissolosVermelhoseutróficos	Lixisols	LX
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicosalumínicos	Cambisols	CM
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicoscarbonáticos	Calcaric Cambisols	CMca
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicosdistroférricos	Dystric Cambisols	CMdy
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicoseutroférricos	Eutric Cambisols	CMeu
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicospetroférricos	Plinthic Cambisols	CMpl
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicossálicos	Salic Cambisols	CMsz
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicossódicos	Sodic Cambisols	CMso
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicosTadistróficos	Dystric Cambisols	CMdy
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicosTaeutróficos	Eutric Cambisols	CMeu

Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicosTbdistróficos	Dystric Cambisols	CMdy
Brazil	Cambissolos	Cambissolos Háplicos	CambissolosHáplicosTbeutróficos	Eutric Cambisols	CMeu
Brazil	Cambissolos	Cambissolos Hísticos	CambissolosHísticosalumínicos	Folic Cambisols	CMfo
Brazil	Cambissolos	Cambissolos Hísticos	CambissolosHísticosdistróficos	Folic Cambisols	CMfo
Brazil	Cambissolos	Cambissolos Húmicos	CambissolosHúmicosalumínicos	Humic Cambisols	CMhu
Brazil	Cambissolos	Cambissolos Húmicos	CambissolosHúmicosalumnoférricos	Humic Cambisols	CMhu
Brazil	Cambissolos	Cambissolos Húmicos	CambissolosHúmicosdistroférricos	Humic Cambisols	CMhu
Brazil	Cambissolos	Cambissolos Húmicos	CambissolosHúmicosdistróficos	Humic Cambisols	CMhu
Brazil	Chernossolos	Chernossolos Argilúvicos	ChernossolosArgilúvicoscarbonáticos	Luvic Calcic Chernozems	CHcclv
Brazil	Chernossolos	Chernossolos Argilúvicos	ChernossolosArgilúvicosférricos	Luvic Phaeozems	PHlv
Brazil	Chernossolos	Chernossolos Argilúvicos	ChernossolosArgilúvicosórticos	Luvic Chernozems	CHlv
Brazil	Chernossolos	Chernossolos Ebânicos	ChernossolosEbânicoscarbonáticos	Calcic Chernic Chernozems	CHchcc
Brazil	Chernossolos	Chernossolos Ebânicos	ChernossolosEbânicosórticos	Chernic Chernozems	CHch
Brazil	Chernossolos	Chernossolos Háplicos	ChernossolosHáplicoscarbonáticos	Calcic Chernozems	CHcc
Brazil	Chernossolos	Chernossolos Háplicos	ChernossolosHáplicosférricos	Phaeozems	PH
Brazil	Chernossolos	Chernossolos Háplicos	ChernossolosHáplicosórticos	Chernozems	CH
Brazil	Chernossolos	Chernossolos Rêndzicos	ChernossolosRêndzicoslíticos	Rendzic Leptosols	LPrz
Brazil	Chernossolos	Chernossolos Rêndzicos	ChernossolosRêndzicosórticos	Rendzic Phaeozems	PHrz
Brazil	Chernossolos	Chernossolos Rêndzicos	ChernossolosRêndzicossaproliticos	Rendzic Phaeozems	PHrz
Brazil	Espodossolos	Espodossolos Cárbicos	EspodossolosCárbicoshidromórficos	Albic Carbic Podzols	PZcbab
Brazil	Espodossolos	Espodossolos Cárbicos	EspodossolosCárbicoshiperespressos	Albic Carbic Podzols	PZcbab
Brazil	Espodossolos	Espodossolos Cárbicos	EspodossolosCárbicosórticos	Albic Carbic Podzols	PZcbab
Brazil	Espodossolos	Espodossolos Ferrilúvicos	EspodossolosFerrilúvicoshidromórficos	Podzols	PZ
Brazil	Espodossolos	Espodossolos Ferrocárbicos	EspodossolosFerrocárbicoshidromórficos	Gleyic Albic Podzols	PZabgl
Brazil	Espodossolos	Espodossolos Ferrocárbicos	EspodossolosFerrocárbicoshiperespressos	Albic Carbic Podzols	PZcbab
Brazil	Espodossolos	Espodossolos Ferrocárbicos	EspodossolosFerrocárbicosórticos	Albic Carbic Podzols	PZcbab
Brazil	Espodossolos	Espodossolos Humilúvico	EspodossolosHumilúvicoshidromórficos	Albic Podzols	PZab
Brazil	Espodossolos	Espodossolos Humilúvico	EspodossolosHumilúvicosórticos	Albic Podzols	PZab
Brazil	Gleissolos	Gleissolos Háplicos	GleissolosHáplicosalumínicos	Gleysols	GL
Brazil	Gleissolos	Gleissolos Háplicos	GleissolosHáplicosTacarbonáticos	Calcic Gleysols	GLcc

Brazil	Gleissolos	Gleissolos Háplicos	GleissolosHáplicosTadistróficos	Dystric Gleysols	GLdy
Brazil	Gleissolos	Gleissolos Háplicos	GleissolosHáplicosTaeutróficos	Eutric Gleysols	GLeu
Brazil	Gleissolos	Gleissolos Háplicos	GleissolosHáplicosTbdistróficos	Dystric Gleysols	GLdy
Brazil	Gleissolos	Gleissolos Háplicos	GleissolosHáplicosTbeutróficos	Eutric Gleysols	GLeu
Brazil	Gleissolos	Gleissolos Melânicos	GleissolosMelânicosalumínicos	Umbric Gleysols	GLum
Brazil	Gleissolos	Gleissolos Melânicos	GleissolosMelânicoscarbonáticos	Calcic Mollic Gleysols	GLmocc
Brazil	Gleissolos	Gleissolos Melânicos	GleissolosMelânicosdistróficos	Umbric Gleysols	GLum
Brazil	Gleissolos	Gleissolos Melânicos	GleissolosMelânicoseutróficos	Mollic Gleysols	GLmo
Brazil	Gleissolos	Gleissolos Sálicos	GleissolosSálicosórticos	Salic Gleysols	GLsz
Brazil	Gleissolos	Gleissolos Sálicos	GleissolosSálicossódicus	Sodic Gleysols	GLso
Brazil	Gleissolos	Gleissolos Tiomórficos	GleissolosTiomórficoshísticos	Thionic Histic Gleysols	GLhiti
Brazil	Gleissolos	Gleissolos Tiomórficos	GleissolosTiomórficoshúmicos	Thionic Humic Gleysols	GLhuti
Brazil	Gleissolos	Gleissolos Tiomórficos	GleissolosTiomórficosórticos	Thionic Gleysols	GLti
Brazil	Latossolos	Latossolos Amarelos	LatossolosAmarelosácricos	Acric Ferrasols	FRac
Brazil	Latossolos	Latossolos Amarelos	LatossolosAmarelosacriférricos	Acric Ferrasols	FRac
Brazil	Latossolos	Latossolos Amarelos	LatossolosAmareloscoesos	Ferrasols	FR
Brazil	Latossolos	Latossolos Amarelos	LatossolosAmarelosdistroférricos	Ferrasols	FR
Brazil	Latossolos	Latossolos Amarelos	LatossolosAmearelosdistróficos	Ferrasols	FR
Brazil	Latossolos	Latossolos Amarelos	LatossolosAmeareloseutróficos	Ferrasols	FR
Brazil	Latossolos	Latossolos Brunos	LatossolosBrunosácricos	Acric Ferrasols	FRac
Brazil	Latossolos	Latossolos Brunos	LatossolosBrunosalumínicos	Ferrasols	FR
Brazil	Latossolos	Latossolos Vermelho-Amarelos	LatossolosVermelho-Amarelosácricos	Acric Ferrasols	FRac
Brazil	Latossolos	Latossolos Vermelho-Amarelos	LatossolosVermelho-Amarelosacriférricos	Acric Ferrasols	FRac
Brazil	Latossolos	Latossolos Vermelho-Amarelos	LatossolosVermelho-Amarelosdistroférricos	Ferrasols	FR
Brazil	Latossolos	Latossolos Vermelho-Amarelos	LatossolosVermelho-Amarelosdistróficos	Geric Ferrasols	FRgr
Brazil	Latossolos	Latossolos Vermelho-Amarelos	LatossolosVermelho-Amareloseutróficos	Ferrasols	FR

Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhosácricos	Acric Ferrasols	FRac
Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhosacriférricos	Acric Ferrasols	FRac
Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhosalumnoférricos	Ferrasols	FR
Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhosdistroférricos	Ferrasols	FR
Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhosdistróficos	Ferrasols	FR
Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhoseutroférricos	Ferrasols	FR
Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhoseutróficos	Ferrasols	FR
Brazil	Latossolos	Latossolos Vermelhos	LatossolosVermelhospetroférricos	Plinthic Ferrasols	FRpl
Brazil	Luvissolos	Luvissolos Crômicos	LuvissolosCrômicoscarbonáticos	Calcic Luvisols	LVcc
Brazil	Luvissolos	Luvissolos Crômicos	LuvissolosCrômicosórticos	Luvisols	LV
Brazil	Luvissolos	Luvissolos Crômicos	LuvissolosCrômicospálicos	Luvisols	LV
Brazil	Luvissolos	Luvissolos Hipocrômicos	LuvissolosHipocrômicoscarbonáticos	Calcic Luvisols	LVcc
Brazil	Luvissolos	Luvissolos Hipocrômicos	LuvissolosHipocrômicosórticos	Luvisols	LV
Brazil	Neossolos	Neossolos Flúvicos	NeossolosFlúvicoscarbonáticos	Calcic Fluvisols	FLcc
Brazil	Neossolos	Neossolos Flúvicos	NeossolosFlúvicospsamíticos	Fluvisols	FL
Brazil	Neossolos	Neossolos Flúvicos	NeossolosFlúvicossálicos	Salic Fluvisols	FLsz
Brazil	Neossolos	Neossolos Flúvicos	NeossolosFlúvicossódicos	Fluvisols	FL
Brazil	Neossolos	Neossolos Flúvicos	NeossolosFlúvicosTaeutróficos	Fluvisols	FL
Brazil	Neossolos	Neossolos Flúvicos	NeossolosFlúvicosTbdistóficos	Fluvisols	FL
Brazil	Neossolos	Neossolos Flúvicos	NeossolosFlúvicosTbeutróficos	Fluvisols	FL
Brazil	Neossolos	Neossolos Litólicos	NeossolosLitólicoscarbonáticos	Calcic Leptosols	LPcc
Brazil	Neossolos	Neossolos Litólicos	NeossolosLitólicosdistróficos	Leptosols	LP
Brazil	Neossolos	Neossolos Litólicos	NeossolosLitólicoseutróficos	Leptosols	LP
Brazil	Neossolos	Neossolos Litólicos	NeossolosLitólicoshísticos	Histic Leptosols	LPhi
Brazil	Neossolos	Neossolos Litólicos	NeossolosLitólicoshúmicos	Umbric Leptosols	LPum
Brazil	Neossolos	Neossolos Litólicos	NeossolosLitólicosPsamíticos	Leptosols	LP
Brazil	Neossolos	Neossolos Quartzarênicos	NeossolosQuartzarênicoshidromórficos	Gleyic Arenosols	ARgl
Brazil	Neossolos	Neossolos Quartzarênicos	NeossolosQuartzarênicosórticos	Arenosols	AR
Brazil	Neossolos	Neossolos Regolíticos	NeossolosRegolíticosdistróficos	Regosols	RG
Brazil	Neossolos	Neossolos Regolíticos	NeossolosRegolíticoseutróficos	Regosols	RG

Brazil	Neossolos	Neossolos Regolíticos	NeossolosRegolíticosPsamíticos	Regosols	RG
Brazil	Nitossolos	Nitossolos Háplicos	NitossolosHáplicosalumínicos	Nitisols	NT
Brazil	Nitossolos	Nitossolos Háplicos	NitossolosHáplicosdistróficos	Nitisols	NT
Brazil	Nitossolos	Nitossolos Háplicos	NitossolosHáplicoseutróficos	Nitisols	NT
Brazil	Nitossolos	Nitossolos Vermelhos	NitossolosVermelhosdistroférricos	Nitisols	NT
Brazil	Nitossolos	Nitossolos Vermelhos	NitossolosVermelhosdistróficos	Nitisols	NT
Brazil	Nitossolos	Nitossolos Vermelhos	NitossolosVermelhoseutroférricos	Nitisols	NT
Brazil	Nitossolos	Nitossolos Vermelhos	NitossolosVermelhoseutróficos	Nitisols	NT
Brazil	Organossolos	Organossolos Fólicos	OrganossolosFólicosfíbricos	Fibric Folic Histosols	HSfofi
Brazil	Organossolos	Organossolos Fólicos	OrganossolosFólicoshêmicos	Hemic Folic Histosols	HSfohm
Brazil	Organossolos	Organossolos Fólicos	OrganossolosFólicossápricos	Sapric Folic Histosols	HSfosa
Brazil	Organossolos	Organossolos Háplicos	OrganossolosHáplicosfibricos	Fibric Histosols	HSfi
Brazil	Organossolos	Organossolos Háplicos	OrganossolosHáplicoshêmicos	Hemic Histosols	HShm
Brazil	Organossolos	Organossolos Háplicos	OrganossolosHáplicossápricos	Sapric Histosols	HSsa
Brazil	Organossolos	Organossolos Mésicos	OrganossolosMésicosfíbricos	Fibric Histosols	HSfi
Brazil	Organossolos	Organossolos Mésicos	OrganossolosMésicoshêmicos	Hemic Histosols	HShm
Brazil	Organossolos	Organossolos Mésicos	OrganossolosMésicossápricos	Sapric Histosols	HSsa
Brazil	Organossolos	Organossolos Tiomórficos	OrganossolosTiomórficosfíbricos	Fibric Histosols	HSfi
Brazil	Organossolos	Organossolos Tiomórficos	OrganossolosTiomórficoshêmicos	Hemic Histosols	HShm
Brazil	Organossolos	Organossolos Tiomórficos	OrganossolosTiomórficossápricos	Sapric Histosols	HSsa
Brazil	Planossolos	Planossolos Háplicos	PlanossolosHáplicosdistróficos	Planosols	PL
Brazil	Planossolos	Planossolos Háplicos	PlanossolosHáplicoseutróficos	Planosols	PL
Brazil	Planossolos	Planossolos Háplicos	PlanossolosHáplicossálicos	Salic Planosols	PLsz
Brazil	Planossolos	Planossolos Hidromórficos	PlanossolosHidromórficosdistróficos	Gleyic Planosols	PLgl
Brazil	Planossolos	Planossolos Hidromórficos	PlanossolosHidromórficoseutróficos	Gleyic Planosols	PLgl
Brazil	Planossolos	Planossolos Hidromórficos	PlanossolosHidromórficossálicos	Salic Gleyic Planosols	PLglsz
Brazil	Planossolos	Planossolos Nátricos	PlanossolosNátricoscarbonáticos	Calcic Sodic Planosols	PLsocc
Brazil	Planossolos	Planossolos Nátricos	PlanossolosNátricosórticos	Sodic Planosols	PLso
Brazil	Planossolos	Planossolos Nátricos	PlanossolosNátricossálicos	Salic Sodic Planosols	PLsosz
Brazil	Plintosolos	Plintossolos Argilúvicos	PlintossolosArgilúvicosalumínicos	Acric Plinthosols	PTac

Brazil	Plintosolos	Plintossolos Argilúvicos	PlintossolosArgilúvicosdistróficos	Acric Plinthosols	PTac
Brazil	Plintosolos	Plintossolos Argilúvicos	PlintossolosArgilúvicoseutróficos	Lixic Plinthosols	PTlx
Brazil	Plintosolos	Plintossolos Háplicos	PlintossolosHáplicosdistróficos	Plinthosols	PT
Brazil	Plintosolos	Plintossolos Háplicos	PlintossolosHáplicoseutróficos	Plinthosols	PT
Brazil	Plintosolos	Plintossolos Pétricos	PlintossolosPétricosconcrecionários	Lithic Plinthosols	PTli
Brazil	Plintosolos	Plintossolos Pétricos	PlintossolosPétricoslitoplínticos	Petric Plinthosols	PTpt
Brazil	Vertissolos	Vertissolos Cromados	VertissolosCromadoscarbonáticos	Calcic Vertisols	VRcc
Brazil	Vertissolos	Vertissolos Cromados	VertissolosCromadosórticos	Vertisols	VR
Brazil	Vertissolos	Vertissolos Cromados	VertissolosCromadossálicos	Salic Vertisols	VRsz
Brazil	Vertissolos	Vertissolos Cromados	VertissolosCromadossódicos	Sodic Vertisols	VRso
Brazil	Vertissolos	Vertissolos Ebânicos	VertissolosEbânicoscarbonáticos	Calcic Vertisols	VRcc
Brazil	Vertissolos	Vertissolos Ebânicos	VertissolosEbânicosórticos	Vertisols	VR
Brazil	Vertissolos	Vertissolos Ebânicos	VertissolosEbânicossódicos	Vertisols	VR
Brazil	Vertissolos	Vertissolos Hidromórficos	VertissolosHidromórficoscarbonáticos	Calcic Gleyic Vertisols	VRglcc
Brazil	Vertissolos	Vertissolos Hidromórficos	VertissolosHidromórficosórticos	Gleyic Vertisols	VRgl
Brazil	Vertissolos	Vertissolos Hidromórficos	VertissolosHidromórficossálicos	Gleyic Salic Vertisols	VRszgl
Brazil	Vertissolos	Vertissolos Hidromórficos	VertissolosHidromórficossódicos	Gleyic Vertisols	VRgl
Canada	Brunisolic	Dystric Brunisol		Dystric Cambisols	CMdy
Canada	Brunisolic	Eutric Brunisol		Eutric Cambisols	CMeu
Canada	Brunisolic	Melanic Brunisol		Cambisols	CM
Canada	Brunisolic	Sombric Brunisol		Umbric Cambisols	CMum
Canada	Chernozemic	Black Chernozem		Chernozems	CH
Canada	Chernozemic	Brown Chernozem		Aridic Kastanozems	KSad
Canada	Chernozemic	Dark Brown Chernozem		Haplic Kastanozems	KSha
Canada	Chernozemic	Dark Gray Chernozem		Greyzemic Chernozems	CHgz
Canada	Cryosolic	Organic Cryosol		Cryic Histosols	HScy
Canada	Cryosolic	Static Cryosol		Cryosols	CR
Canada	Cryosolic	Turbic Cryosol		Turbic Cryosols	CRtu
Canada	Gleysolic	Gleysol		Gleysols	GL
Canada	Gleysolic	Humic Gleysol		Mollic Gleysols	GLmo

Canada	Gleysolic	Luvic Gleysol		Planosols	PL
Canada	Luvisolic	Gray Brown Luvisol		Albic Luvisols	LVab
Canada	Luvisolic	Gray Luvisol		Albic Luvisols	LVab
Canada	Organic	Fibrisol		Fibric Histosols	HSfi
Canada	Organic	Folisol		Folic Histosols	HSfo
Canada	Organic	Humisol		Hyperhumic Histosols	HSjh
Canada	Organic	Mesisol		Hemic Histosols	HShm
Canada	Podzolic	Ferro-Humic Podzol		Podzols	PZ
Canada	Podzolic	Humic Podzol		Humic Podzols	PZhu
Canada	Podzolic	Humo-Ferric Podzol		Podzols	PZ
Canada	Regosolic	Humic Regosol		Fluvisols	FL
Canada	Regosolic	Regosol		Regosols	RG
Canada	Solonetzic	Solod		Planosols	PL
Canada	Solonetzic	Solodized Solonetz		Mollic Solonetz	SNmo
Canada	Solonetzic	Solonetz		Mollic Solonetz	SNmo
Canada	Solonetzic	Vertic Solonetz		Sodic Vertisols	VRso
Canada	Vertisolic	Humic Vertisol		Dystric Vertisols	VRdy
Canada	Vertisolic	Vertisol		Vertisols	VR
NewZealand	Allophanic Soils	Gley Allophanic Soils		Gleyic Andosols	ANgl
NewZealand	Allophanic Soils	Impeded Allophanic Soils		Petroduric Andosols	ANpd
NewZealand	Allophanic Soils	Orthic Allophanic Soils		Andosols	AN
NewZealand	Allophanic Soils	Perch-gley Allophanic Soils		Stagnic Andosols	ANst
NewZealand	Anthropic Soils	Fill Anthropic Soils		Hortic Anthrosols	ATht
NewZealand	Anthropic Soils	Mixed Anthropic Soils		Plaggic Anthrosols	ATpa
NewZealand	Anthropic Soils	Refuse Anthropic Soils		Terric Anthrosols	ATtr
NewZealand	Anthropic Soils	Truncated Anthropic Soils		Regosols	RG
NewZealand	Brown Soils	Acid Brown Soils		Cambisols	CM
NewZealand	Brown Soils	Allophanic Brown Soils		Andic Cambisols	CMan
NewZealand	Brown Soils	Firm Brown Soils		Fragic Cambisols	CMfg
NewZealand	Brown Soils	Mafic Brown Soils		Cambisols	CM

NewZealand	Brown Soils	Orthic Brown Soils		Cambisols	CM
NewZealand	Brown Soils	Oxidic Brown Soils		Ferralic Cambisols	CMfl
NewZealand	Brown Soils	Sandy Brown Soils		Brunic Arenosols	ARbr
NewZealand	Gley Soils	Acid Gley Soils		Gleysols	GL
NewZealand	Gley Soils	Orthic Gley Soils		Gleysols	GL
NewZealand	Gley Soils	Oxidic Gley Soils		Plinthic Gleysols	GLpl
NewZealand	Gley Soils	Recent Gley Soils		Gleyic Fluvisols	FLgl
NewZealand	Gley Soils	Sandy Gley Soils		Gleysols	GL
NewZealand	Gley Soils	Sulphuric Gley Soils		Gleysols	GL
NewZealand	Granular Soils	Melanic Granular Soils		Umbric Luvisols	LVum
NewZealand	Granular Soils	Orthic Granular Soils		Luvisols	LV
NewZealand	Granular Soils	Oxidic Granular Soils		Luvisols	LV
NewZealand	Granular Soils	Perch-gley Granular Soils		Stagnic Luvisols	LVst
NewZealand	Melanic Soils	Mafic Melanic Soils		Chernozems	CH
NewZealand	Melanic Soils	Orthic Melanic Soils		Chernozems	CH
NewZealand	Melanic Soils	Perch-gley Melanic Soils		Stagnic Chernozems	CHst
NewZealand	Melanic Soils	Rendzic Melanic Soils		Rendzic Leptosols	LPrz
NewZealand	Melanic Soils	Vertic Melanic Soils		Vertisols	VR
NewZealand	Organic Soils	Fibric Organic Soils		Fibric Histosols	HSfi
NewZealand	Organic Soils	Humic Organic Soils		Sapric Histosols	HSsa
NewZealand	Organic Soils	Litter Organic Soils		Folic Histosols	HSfo
NewZealand	Organic Soils	Mesic Organic Soils		Hemic Histosols	HShm
NewZealand	Oxidic Soils	Nodular Oxidic Soils		Ferrasols	FR
NewZealand	Oxidic Soils	Orthic Oxidic Soils		Ferrasols	FR
NewZealand	Oxidic Soils	Perch-gley Oxidic Soils		Stagnic Plinthosols	PTst
NewZealand	Pallic Soils	Argillic Pallic Soils		Luvic Planosols	PLlv
NewZealand	Pallic Soils	Duric Pallic Soils		Duric Planosols	PLdu
NewZealand	Pallic Soils	Fragic Pallic Soils		Fragic Planosols	PLfg
NewZealand	Pallic Soils	Immature Pallic Soils		Abruptic Planosols	PLap
NewZealand	Pallic Soils	Laminar Pallic Soils		Lamellic Planosols	PLll

NewZealand	Pallic Soils	Perch-gley Pallic Soils		Stagnic Planosols	PLst
NewZealand	Podzols	Densipan Podzols		Albic Podzols	PZab
NewZealand	Podzols	Groundwater-gley Podzols		Gleyic Albic Podzols	PZabgl
NewZealand	Podzols	Orthic Podzols		Albic Podzols	PZab
NewZealand	Podzols	Pan Podzols		Albic Ortsteinic Podzols	PZosab
NewZealand	Podzols	Perch-gley Podzols		Stagnic Albic Podzols	PZabst
NewZealand	Pumice Soils	Impeded Pumice Soils		Duric Vitric Andosols	ANvidu
NewZealand	Pumice Soils	Orthic Pumice Soils		Vitric Andosols	ANvi
NewZealand	Pumice Soils	Perch-gley Pumice Soils		Stagnic Vitric Andosols	ANvist
NewZealand	Raw Soils	Fluvial Raw Soils		Protic Fluvisols	FLpr
NewZealand	Raw Soils	Gley Raw Soils		Gleysols	GL
NewZealand	Raw Soils	Hydrothermal Raw Soils		Regosols	RG
NewZealand	Raw Soils	Orthic Raw Soils		Regosols	RG
NewZealand	Raw Soils	Rocky Raw Soils		Leptosols	LP
NewZealand	Raw Soils	Sandy Raw Soils		Protic Arenosols	ARpr
NewZealand	Raw Soils	Tephric Raw Soils		Regosols	RG
NewZealand	Recent Soils	Fluvial Recent Soils		Fluvisols	FL
NewZealand	Recent Soils	Hydrothermal Recent Soils		Regosols	RG
NewZealand	Recent Soils	Orthic Recent Soils		Regosols	RG
NewZealand	Recent Soils	Rocky Recent Soils		Leptosols	LP
NewZealand	Recent Soils	Sandy Recent Soils		Arenosols	AR
NewZealand	Recent Soils	Tephric Recent Soils		Regosols	RG
NewZealand	Semiarid Soils	Aged-argillic Semiarid Soils		Luvisols	LV
NewZealand	Semiarid Soils	Argillic Semiarid Soils		Luvisols	LV
NewZealand	Semiarid Soils	Immature Semiarid Soils		Cambisols	CM
NewZealand	Semiarid Soils	Solonetzic Semiarid Soils		Solonetz	SN
NewZealand	Ultic Soils	Albic Ultic Soils		Acrisols	AC
NewZealand	Ultic Soils	Densipan Ultic Soils		Acrisols	AC
NewZealand	Ultic Soils	Perch-gley Ultic Soils		Stagnic Acrisols	ACst
NewZealand	Ultic Soils	Sandy Ultic Soils		Acrisols	AC

NewZealand	Ultic Soils	Yellow Ultic Soils		Acrisols	AC
UnitedStates	Alfisols	Aqualfs	Albaqualfs	Albic Planosols	PLab
UnitedStates	Alfisols	Aqualfs	Cryaqualfs	Gelic Planosols	PLge
UnitedStates	Alfisols	Aqualfs	Duraqualfs	Planosols	PL
UnitedStates	Alfisols	Aqualfs	Endoaqualfs	Gleyic Luvisols	LVgl
UnitedStates	Alfisols	Aqualfs	Epiaqualfs	Haplic Stagnosols	STha
UnitedStates	Alfisols	Aqualfs	Fragiaqualfs	Fragic Planosols	PLfg
UnitedStates	Alfisols	Aqualfs	Glossaqualfs	Stagnic Albeluvisols	ABst
UnitedStates	Alfisols	Aqualfs	Kandiaqualfs	Planosols	PL
UnitedStates	Alfisols	Aqualfs	Natraqualfs	Stagnic Solonetz	SNst
UnitedStates	Alfisols	Aqualfs	Ochraqualfs	Luvisols	LV
UnitedStates	Alfisols	Aqualfs	Plintaqualfs	Plinthic Planosols	PLpl
UnitedStates	Alfisols	Aqualfs	Umbraqualfs	Umbric Planosols	PLum
UnitedStates	Alfisols	Aqualfs	Vermaqualfs	Vermic Planosols	PLvm
UnitedStates	Alfisols	Boralfs	Cryoboralfs	Albeluvisols	AB
UnitedStates	Alfisols	Boralfs	Eutroboralfs	Eutric Albeluvisols	ABeu
UnitedStates	Alfisols	Boralfs	Paleboralfs	Albeluvisols	AB
UnitedStates	Alfisols	Cryalfs	Glossocryalfs	Albeluvisols	AB
UnitedStates	Alfisols	Cryalfs	Haplocryalfs	Luvisols	LV
UnitedStates	Alfisols	Cryalfs	Palecryalfs	Albeluvisols	AB
UnitedStates	Alfisols	Udalfs	Ferrudalfs	Ferric Albeluvisols	ABfr
UnitedStates	Alfisols	Udalfs	Fragiudalfs	Fragic Luvisols	LVfg
UnitedStates	Alfisols	Udalfs	Fraglossudalfs	Fragic Albeluvisols	ABfg
UnitedStates	Alfisols	Udalfs	Glossudalfs	Albeluvisols	AB
UnitedStates	Alfisols	Udalfs	Hapludalfs	Luvisols	LV
UnitedStates	Alfisols	Udalfs	Kandiudalfs	Profondic Lixisols	LXpn
UnitedStates	Alfisols	Udalfs	Kanhapludalfs	Lixisols	LX
UnitedStates	Alfisols	Udalfs	Natrudalfs	Solonetz	SN
UnitedStates	Alfisols	Udalfs	Paleudalfs	Luvisols	LV
UnitedStates	Alfisols	Udalfs	Rhodudalfs	Rhodic Luvisols	LVro

UnitedStates	Alfisols	Udalfs	Tropudalfs	Luvisols	LV
UnitedStates	Alfisols	Ustalfs	Durustalfs	Luvic Petric Durisols	DUptlv
UnitedStates	Alfisols	Ustalfs	Haplustalfs	Luvisols	LV
UnitedStates	Alfisols	Ustalfs	Kandiustalfs	Profondic Lixisols	LXpn
UnitedStates	Alfisols	Ustalfs	Kanhaplustalfs	Lixisols	LX
UnitedStates	Alfisols	Ustalfs	Natrustalfs	Solonetz	SN
UnitedStates	Alfisols	Ustalfs	Paleustalfs	Rhodic Profondic Luvisols	LVpnro
UnitedStates	Alfisols	Ustalfs	Plinthustalfs	Lixic Plinthosols	PTlx
UnitedStates	Alfisols	Ustalfs	Rhodustalfs	Rhodic Luvisols	LVro
UnitedStates	Alfisols	Xeralfs	Durixeralfs	Petric Luvic Durisols	DUlvpt
UnitedStates	Alfisols	Xeralfs	Fragixeralfs	Fragic Luvisols	LVfg
UnitedStates	Alfisols	Xeralfs	Haploxeralfs	Haplic Luvisols	LVha
UnitedStates	Alfisols	Xeralfs	Natrixeralfs	Solonetz	SN
UnitedStates	Alfisols	Xeralfs	Palexeralfs	Petrocalcic Luvisols	LVpc
UnitedStates	Alfisols	Xeralfs	Plintoxeralfs	Lixic Plinthosols	PTlx
UnitedStates	Alfisols	Xeralfs	Rhodoxeralfs	Rhodic Luvisols	LVro
UnitedStates	Andisols	Aquands	Cryaquands	Histic Andosols	ANhi
UnitedStates	Andisols	Aquands	Duraquands	Petroduric Histic Andosols	ANhipd
UnitedStates	Andisols	Aquands	Endoaquands	Gleyic Andosols	ANgl
UnitedStates	Andisols	Aquands	Epiaquands	Stagnic Andosols	ANst
UnitedStates	Andisols	Aquands	Haplaquands	Andosols	AN
UnitedStates	Andisols	Aquands	Melanaquands	Gleyic Melanic Andosols	ANmlgl
UnitedStates	Andisols	Aquands	Placaquands	Placic Gleyic Andosols	ANglpi
UnitedStates	Andisols	Aquands	Vitraquands	Gleyic Vitric Andosols	ANvigl
UnitedStates	Andisols	Cryands	Duricryands	Petroduric Andosols	ANpd
UnitedStates	Andisols	Cryands	Fulvicryands	Fulvic Andosols	ANfu
UnitedStates	Andisols	Cryands	Haplocryands	Andosols	AN
UnitedStates	Andisols	Cryands	Hydrocryands	Hydric Andosols	ANhy
UnitedStates	Andisols	Cryands	Melanocryands	Melanic Andosols	ANml
UnitedStates	Andisols	Cryands	Vitricryands	Vitric Andosols	ANvi

UnitedStates	Andisols	Torrands	Duritorrands	Petroduric Andosols	ANpd
UnitedStates	Andisols	Torrands	Haplotorrands	Andosols	AN
UnitedStates	Andisols	Torrands	Vitritorrands	Vitric Andosols	ANvi
UnitedStates	Andisols	Udands	Durudands	Petroduric Andosols	ANpd
UnitedStates	Andisols	Udands	Fulvudands	Fulvic Andosols	ANfu
UnitedStates	Andisols	Udands	Hapludands	Andosols	AN
UnitedStates	Andisols	Udands	Hydrudands	Hydric Andosols	ANhy
UnitedStates	Andisols	Udands	Melanudands	Melanic Andosols	ANml
UnitedStates	Andisols	Udands	Placudands	Placic Andosols	ANpi
UnitedStates	Andisols	Ustands	Durustands	Petroduric Andosols	ANpd
UnitedStates	Andisols	Ustands	Haplustands	Andosols	AN
UnitedStates	Andisols	Vitrands	Udivitrands	Vitric Andosols	ANvi
UnitedStates	Andisols	Vitrands	Ustivitrands	Vitric Andosols	ANvi
UnitedStates	Andisols	Xerands	Haploxerands	Andosols	AN
UnitedStates	Andisols	Xerands	Melanoxerands	Melanic Andosols	ANml
UnitedStates	Andisols	Xerands	Vitrixerands	Vitric Andosols	ANvi
UnitedStates	Aridisols	Argids	Calciargids	Calcic Luvisols	LVcc
UnitedStates	Aridisols	Argids	Duragids	Duric Luvisols	LVdu
UnitedStates	Aridisols	Argids	Gypsiargids	Gypsic Luvisols	LVgy
UnitedStates	Aridisols	Argids	Haplargids	Luvisols	LV
UnitedStates	Aridisols	Argids	Nadurargids	Duric Solonetz	SNdu
UnitedStates	Aridisols	Argids	Natrargids	Solonetz	SN
UnitedStates	Aridisols	Argids	Paleargids	Profondic Luvisols	LVpn
UnitedStates	Aridisols	Argids	Petroargids	Petrocalcic Luvisols	LVpc
UnitedStates	Aridisols	Calcids	Haplocalcids	Calcisols	CL
UnitedStates	Aridisols	Calcids	Petrocalcids	Petric Calcisols	CLpt
UnitedStates	Aridisols	Cambids	Anthracambids	Irragric Anthrosols	ATir
UnitedStates	Aridisols	Cambids	Aquicambids	Gleyic Cambisols	CMgl
UnitedStates	Aridisols	Cambids	Camborthids	Cambisols	CM
UnitedStates	Aridisols	Cambids	Haplocambids	Cambisols	CM

UnitedStates	Aridisols	Cambids	Haploxerepts	Calcic Cambisols	CMcc
UnitedStates	Aridisols	Cambids	Petrocambids	Cambisols	CM
UnitedStates	Aridisols	Cryids	Argicryids	Profondic Solonetz	SNpn
UnitedStates	Aridisols	Cryids	Calcicryids	Calcisols	CL
UnitedStates	Aridisols	Cryids	Gypsicryids	Gypsisols	Gy
UnitedStates	Aridisols	Cryids	Haplocryids	Cambisols	CM
UnitedStates	Aridisols	Cryids	Petrocryids	Petric Calcisols	CLpt
UnitedStates	Aridisols	Cryids	Salicryids	Solonchaks	SC
UnitedStates	Aridisols	Durids	Argidurids	Luvic Petric Durisols	DUptlv
UnitedStates	Aridisols	Durids	Haplodurids	Petric Durisols	DUpt
UnitedStates	Aridisols	Durids	Natridurids	Petroduric Solonetz	SNpd
UnitedStates	Aridisols	Gypsids	Argigypsids	Luvic Gypsisols	Gylv
UnitedStates	Aridisols	Gypsids	Calcigypsids	Calcic Gypsisols	Gycc
UnitedStates	Aridisols	Gypsids	Haplogypsids	Gypsisols	Gy
UnitedStates	Aridisols	Gypsids	Natrigypsids	Gypsic Solonetz	SNgy
UnitedStates	Aridisols	Gypsids	Petrogypsids	Petric Gypsisols	Gypt
UnitedStates	Aridisols	Orthids	Calciorthids	Calcisols	CL
UnitedStates	Aridisols	Orthids	Durorthids	Duric Solonchaks	SCdu
UnitedStates	Aridisols	Orthids	Gypsiorthids	Gypsic Solonchaks	SCgy
UnitedStates	Aridisols	Orthids	Paleorthids	Calcisols	CL
UnitedStates	Aridisols	Orthids	Salorthids	Solonchaks	SC
UnitedStates	Aridisols	Salids	Aquisalids	Gleyic Solonchaks	SCgl
UnitedStates	Aridisols	Salids	Haplosalids	Solonchaks	SC
UnitedStates	Entisols	Aquents	Cryaquents	Gleysols	GL
UnitedStates	Entisols	Aquents	Endoaquents	Gleysols	GL
UnitedStates	Entisols	Aquents	Epiaquents	Stagnosols	ST
UnitedStates	Entisols	Aquents	Fluvaquents	Gleyic Fluvisols	FLgl
UnitedStates	Entisols	Aquents	Gelaquents	Gelic Gleysols	GLge
UnitedStates	Entisols	Aquents	Haplaquents	Gleysols	GL
UnitedStates	Entisols	Aquents	Hydraquents	Fluvisols	FL

UnitedStates	Entisols	Aquents	Psammaquents	Arenic Gleysols	GLar
UnitedStates	Entisols	Aquents	Sulfaquents	Thionic Gleysols	GLti
UnitedStates	Entisols	Aquents	Tropaquents	Gleysols	GL
UnitedStates	Entisols	Arents	Arents	Regosols	RG
UnitedStates	Entisols	Arents	Torriarents	Irragric Anthrosols	ATir
UnitedStates	Entisols	Arents	Udarents	Anthrosols	AT
UnitedStates	Entisols	Arents	Ustarents	Anthrosols	AT
UnitedStates	Entisols	Arents	Xerarents	Irragric Anthrosols	ATir
UnitedStates	Entisols	Fluvents	Cryofluvents	Fluvisols	FL
UnitedStates	Entisols	Fluvents	Gelifluvents	Gelic Fluvisols	FLge
UnitedStates	Entisols	Fluvents	Torrifluvents	Fluvisols	FL
UnitedStates	Entisols	Fluvents	Tropofluvents	Fluvisols	FL
UnitedStates	Entisols	Fluvents	Udifluvents	Fluvisols	FL
UnitedStates	Entisols	Fluvents	Ustifluvents	Fluvisols	FL
UnitedStates	Entisols	Fluvents	Xerofluvents	Haplic Fluvisols	FLha
UnitedStates	Entisols	Orthens	Troporthens	Regosols	RG
UnitedStates	Entisols	Orthents	Cryorthents	Regosols	RG
UnitedStates	Entisols	Orthents	Gelorthents	Gelic Regosols	RGge
UnitedStates	Entisols	Orthents	Torriorthents	Regosols	RG
UnitedStates	Entisols	Orthents	Troporthents	Regosols	RG
UnitedStates	Entisols	Orthents	Udorthents	Regosols	RG
UnitedStates	Entisols	Orthents	Ustorthents	Regosols	RG
UnitedStates	Entisols	Orthents	Xerorthents	Regosols	RG
UnitedStates	Entisols	Psamments	Cryopsamments	Arenosols	AR
UnitedStates	Entisols	Psamments	Quartzipsamments	Arenosols	AR
UnitedStates	Entisols	Psamments	Torripsamments	Arenosols	AR
UnitedStates	Entisols	Psamments	Tropopsamments	Arenosols	AR
UnitedStates	Entisols	Psamments	Udipsamments	Arenosols	AR
UnitedStates	Entisols	Psamments	Ustipsamments	Arenosols	AR
UnitedStates	Entisols	Psamments	Xeropsamments	Arenosols	AR

UnitedStates	Entisols	Usterts	Pelloxererts	Vertisols	VR
UnitedStates	Entisols	Wassents	Fluviwassents	Subaquatic Fluvisols	FLsq
UnitedStates	Entisols	Wassents	Frasiwassents	Subaquatic Fluvisols	FLsq
UnitedStates	Entisols	Wassents	Haplowassents	Subaquatic Fluvisols	FLsq
UnitedStates	Entisols	Wassents	Hydrowassents	Subaquatic Fluvisols	FLsq
UnitedStates	Entisols	Wassents	Psammowassents	Subaquatic Fluvisols	FLsq
UnitedStates	Entisols	Wassents	Sulfiwassents	Thionic Subaquatic Fluvisols	FLsqti
UnitedStates	Gelisols	Histels	Fibrihistels	Cryic Fibric Histosols	HSficy
UnitedStates	Gelisols	Histels	Fibristels	Gelic Fibric Histosols	HSfige
UnitedStates	Gelisols	Histels	Folistels	Cryic Folic Histosols	HSfocy
UnitedStates	Gelisols	Histels	Glacistels	Cryic Glacic Histosols	HSgccy
UnitedStates	Gelisols	Histels	Hemistels	Gelic Hemic Histosols	HShmge
UnitedStates	Gelisols	Histels	Hermistels	Cryic Hemic Histosols	HShmcy
UnitedStates	Gelisols	Histels	Sapristels	Cryic Sapric Histosols	HSsacy
UnitedStates	Gelisols	Orthels	Anhyorthels	Aridic Cryosols	CRad
UnitedStates	Gelisols	Orthels	Aquorthels	Reductaquic Cryosols	CRra
UnitedStates	Gelisols	Orthels	Argiorthels	Luvic Cryosols	CRlv
UnitedStates	Gelisols	Orthels	Haplorthels	Cryosols	CR
UnitedStates	Gelisols	Orthels	Historthels	Histic Cryosols	CRhi
UnitedStates	Gelisols	Orthels	Mollorthels	Mollic Cryosols	CRmo
UnitedStates	Gelisols	Orthels	Psammorthels	Arenic Cryosols	CRar
UnitedStates	Gelisols	Orthels	Umbrorthels	Umbric Cryosols	CRum
UnitedStates	Gelisols	Turbels	Anhyturbels	Aridic Turbic Cryosols	CRtuad
UnitedStates	Gelisols	Turbels	Aquiturbels	Reductaquic Turbic Cryosols	CRtura
UnitedStates	Gelisols	Turbels	Haploturbels	Turbic Cryosols	CRtu
UnitedStates	Gelisols	Turbels	Histoturbels	Histic Turbic Cryosols	CRtuhi
UnitedStates	Gelisols	Turbels	Molliturbels	Mollic Turbic Cryosols	CRtumo
UnitedStates	Gelisols	Turbels	Psammoturbels	Arenic Turbic Cryosols	CRtuar
UnitedStates	Gelisols	Turbels	Umbriturbels	Umbric Turbic Cryosols	CRtuum
UnitedStates	Histosols	Fibrists	Borofibrists	Fibric Histosols	HSfi

UnitedStates	Histosols	Fibrists	Cryofibrists	Fibric Histosols	HSfi
UnitedStates	Histosols	Fibrists	Haplofibrists	Fibric Histosols	HSfi
UnitedStates	Histosols	Fibrists	Medifibrists	Fibric Histosols	HSfi
UnitedStates	Histosols	Fibrists	Sphagnofibrists	Ombric Fibric Histosols	HSfiom
UnitedStates	Histosols	Fibrists	Tropofibrists	Fibric Histosols	HSfi
UnitedStates	Histosols	Folists	Cryofolists	Folic Histosols	HSfo
UnitedStates	Histosols	Folists	Torrifolists	Folic Histosols	HSfo
UnitedStates	Histosols	Folists	Tropofolists	Folic Histosols	HSfo
UnitedStates	Histosols	Folists	Udifolists	Folic Histosols	HSfo
UnitedStates	Histosols	Folists	Ustifolists	Folic Histosols	HSfo
UnitedStates	Histosols	Hemists	Borohemists	Hemic Histosols	HShm
UnitedStates	Histosols	Hemists	Cryohemists	Hemic Histosols	HShm
UnitedStates	Histosols	Hemists	Haplohemists	Hemic Histosols	HShm
UnitedStates	Histosols	Hemists	Medihemists	Hemic Histosols	HShm
UnitedStates	Histosols	Hemists	Sulfihemists	Thionic Hemic Histosols	HShmti
UnitedStates	Histosols	Hemists	Sulfohemists	Thionic Hemic Histosols	HShmti
UnitedStates	Histosols	Hemists	Tropohemists	Hemic Histosols	HShm
UnitedStates	Histosols	Saprists	Borosaprists	Sapric Histosols	HSsa
UnitedStates	Histosols	Saprists	Cryosaprists	Sapric Histosols	HSsa
UnitedStates	Histosols	Saprists	Haplosaprists	Sapric Histosols	HSsa
UnitedStates	Histosols	Saprists	Medisaprists	Sapric Histosols	HSsa
UnitedStates	Histosols	Saprists	Sulfisaprists	Thionic Sapric Histosols	HSsati
UnitedStates	Histosols	Saprists	Sulfosaprists	Thionic Sapric Histosols	HSsati
UnitedStates	Histosols	Wassists	Frasiwassists	Subaquatic Histosols	HSsq
UnitedStates	Histosols	Wassists	Haplowassists	Subaquatic Histosols	HSsq
UnitedStates	Histosols	Wassists	Sulfiwassists	Thionic Subaquatic Histosols	HSsqti
UnitedStates	Inceptisols	Andepts	Dystrandepts	Andosols	AN
UnitedStates	Inceptisols	Andepts	Eutrandepts	Andosols	AN
UnitedStates	Inceptisols	Andepts	Hydrandepts	Andosols	AN
UnitedStates	Inceptisols	Andepts	Vitrandepts	Andosols	AN

UnitedStates	Inceptisols	Anthrepts	Haplanthrepts	Anthric Umbrisols	UMak
UnitedStates	Inceptisols	Anthrepts	Plagganthrepts	Plaggic Anthrosols	ATpa
UnitedStates	Inceptisols	Aquepts	Andaquepts	Gleyic Andosols	ANgl
UnitedStates	Inceptisols	Aquepts	Cryaquepts	Gleysols	GL
UnitedStates	Inceptisols	Aquepts	Endoaquepts	Gleysols	GL
UnitedStates	Inceptisols	Aquepts	Epiaquepts	Stagnosols	ST
UnitedStates	Inceptisols	Aquepts	Fragaquepts	Fragic Gleysols	GLfg
UnitedStates	Inceptisols	Aquepts	Gelaquepts	Gelic Gleysols	GLge
UnitedStates	Inceptisols	Aquepts	Halaquepts	Gleyic Solonchaks	SCgl
UnitedStates	Inceptisols	Aquepts	Haplaquepts	Gleysols	GL
UnitedStates	Inceptisols	Aquepts	Humaquepts	Histic Gleysols	GLhi
UnitedStates	Inceptisols	Aquepts	Petraquepts	Petroplinthic Gleysols	GLpp
UnitedStates	Inceptisols	Aquepts	Sulfaquepts	Thionic Gleysols	GLti
UnitedStates	Inceptisols	Aquepts	Tropaquepts	Gleysols	GL
UnitedStates	Inceptisols	Aquepts	Vermaquepts	Vermic Gleysols	GLvm
UnitedStates	Inceptisols	Cryepts	Calcicryepts	Calcic Cambisols	CMcc
UnitedStates	Inceptisols	Cryepts	Cryochrepts	Cambisols	CM
UnitedStates	Inceptisols	Cryepts	Dystrocryepts	Dystric Cambisols	CMdy
UnitedStates	Inceptisols	Cryepts	Eutrocryepts	Eutric Cambisols	CMeu
UnitedStates	Inceptisols	Cryepts	Haplocryepts	Cambisols	CM
UnitedStates	Inceptisols	Cryepts	Humicryepts	Humic Cambisols	CMhu
UnitedStates	Inceptisols	Gelepts	Dystrogelepts	Gelic Cambisols	CMge
UnitedStates	Inceptisols	Gelepts	Eutrogelepts	Gelic Cambisols	CMge
UnitedStates	Inceptisols	Gelepts	Haplogelepts	Gelic Cambisols	CMge
UnitedStates	Inceptisols	Ochrepts	Durochrepts	Duric Cambisols	CMdu
UnitedStates	Inceptisols	Ochrepts	Ustochrepts	Cambisols	CM
UnitedStates	Inceptisols	Ochrepts	Xerochrepts	Cambisols	CM
UnitedStates	Inceptisols	Tropepts	Dystropepts	Dystric Cambisols	CMdy
UnitedStates	Inceptisols	Tropepts	Humitropepts	Humic Cambisols	CMhu
UnitedStates	Inceptisols	Udepts	Durudepts	Petric Durisols	DUpt

UnitedStates	Inceptisols	Udepts	Dystrochrepts	Cambisols	CM
UnitedStates	Inceptisols	Udepts	Dystrudepts	Dystric Cambisols	CMdy
UnitedStates	Inceptisols	Udepts	Eutrochrepts	Cambisols	CM
UnitedStates	Inceptisols	Udepts	Eutrudepts	Eutric Cambisols	CMeu
UnitedStates	Inceptisols	Udepts	Fragiudepts	Fragic Cambisols	CMfg
UnitedStates	Inceptisols	Udepts	Humudepts	Humic Cambisols	CMhu
UnitedStates	Inceptisols	Udepts	Sulfudepts	Thionic Cambisols	CMti
UnitedStates	Inceptisols	Umbrepts	Cryumbrepts	Umbrisols	UM
UnitedStates	Inceptisols	Umbrepts	Fragiumbrepts	Densic Umbrisols	UMdn
UnitedStates	Inceptisols	Umbrepts	Haplumbrepts	Umbrisols	UM
UnitedStates	Inceptisols	Umbrepts	Xerumbrepts	Umbrisols	UM
UnitedStates	Inceptisols	Ustepts	Calciustepts	Calcisols	CL
UnitedStates	Inceptisols	Ustepts	Duriustepts	Petric Durisols	DUpt
UnitedStates	Inceptisols	Ustepts	Dystrustepts	Dystric Cambisols	CMdy
UnitedStates	Inceptisols	Ustepts	Haplustepts	Cambisols	CM
UnitedStates	Inceptisols	Ustepts	Humustepts	Humic Cambisols	CMhu
UnitedStates	Inceptisols	Xerepts	Calcixerepts	Calcisols	CL
UnitedStates	Inceptisols	Xerepts	Durixerepts	Petric Durisols	DUpt
UnitedStates	Inceptisols	Xerepts	Dystroxerepts	Dystric Cambisols	CMdy
UnitedStates	Inceptisols	Xerepts	Fragixerepts	Fragic Cambisols	CMfg
UnitedStates	Inceptisols	Xerepts	Humixerepts	Humic Cambisols	CMhu
UnitedStates	Mollisols	Albolls	Argialbolls	Luvic Albic Phaeozems	PHablv
UnitedStates	Mollisols	Albolls	Natrialbolls	Mollic Albic Solonetz	SNabmo
UnitedStates	Mollisols	Aquolls	Argiaquolls	Luvic Gleyic Chernozems	CHgllv
UnitedStates	Mollisols	Aquolls	Calciaquolls	Gleyic Chernozems	CHgl
UnitedStates	Mollisols	Aquolls	Cryaquolls	Gleyic Chernozems	CHgl
UnitedStates	Mollisols	Aquolls	Duraquolls	Petroduric Gleyic Chernozems	CHglpd
UnitedStates	Mollisols	Aquolls	Endoaquolls	Gleyic Phaeozems	PHgl
UnitedStates	Mollisols	Aquolls	Epiaquolls	Stagnic Phaeozems	PHst

UnitedStates	Mollisols	Aquolls	Haplaquolls	Gleyic Chernozems	CHgl
UnitedStates	Mollisols	Aquolls	Natraquolls	Mollic Gleyic Solonetz	SNglmo
UnitedStates	Mollisols	Borolls	Argiborolls	Luvic Kastanozems	KSlv
UnitedStates	Mollisols	Borolls	Calciborolls	Calcic Kastanozems	KScc
UnitedStates	Mollisols	Borolls	Cryoborolls	Kastanozems	KS
UnitedStates	Mollisols	Borolls	Haploborolls	Kastanozems	KS
UnitedStates	Mollisols	Borolls	Natriborolls	Mollic Solonetz	SNmo
UnitedStates	Mollisols	Borolls	Paleborolls	Luvic Kastanozems	KSlv
UnitedStates	Mollisols	Cryolls	Argicryolls	Luvic Kastanozems	KSlv
UnitedStates	Mollisols	Cryolls	Calcicryolls	Calcic Kastanozems	KScc
UnitedStates	Mollisols	Cryolls	Duricryolls	Petroduric Kastanozems	KSpd
UnitedStates	Mollisols	Cryolls	Haplocryolls	Kastanozems	KS
UnitedStates	Mollisols	Cryolls	Natricryolls	Mollic Solonetz	SNmo
UnitedStates	Mollisols	Cryolls	Palecryolls	Luvic Kastanozems	KSlv
UnitedStates	Mollisols	Gelolls	Haplogellols	Gelic Kastanozems	KSge
UnitedStates	Mollisols	Rendolls	Cryrendolls	Rendzic Leptosols	LPrz
UnitedStates	Mollisols	Rendolls	Haprendolls	Rendzic Leptosols	LPrz
UnitedStates	Mollisols	Rendolls	Rendolls	Rendzic Leptosols	LPrz
UnitedStates	Mollisols	Udolls	Argiudolls	Luvic Phaeozems	PHlv
UnitedStates	Mollisols	Udolls	Calciudolls	Calcic Phaeozems	PHcc
UnitedStates	Mollisols	Udolls	Hapludolls	Phaeozems	PH
UnitedStates	Mollisols	Udolls	Natrudolls	Mollic Solonetz	SNmo
UnitedStates	Mollisols	Udolls	Paleudolls	Profondic Luvic Phaeozems	PHlvpn
UnitedStates	Mollisols	Udolls	Vermiudolls	Vermic Chernozems	CHvm
UnitedStates	Mollisols	Ustolls	Argiustolls	Luvic Phaeozems	PHlv
UnitedStates	Mollisols	Ustolls	Calciustolls	Calcic Chernozems	CHcc
UnitedStates	Mollisols	Ustolls	Durustolls	Petroduric Chernozems	CHpd
UnitedStates	Mollisols	Ustolls	Haplustolls	Phaeozems	PH
UnitedStates	Mollisols	Ustolls	Natrustolls	Mollic Solonetz	SNmo
UnitedStates	Mollisols	Ustolls	Paleustolls	Profondic Luvic Phaeozems	PHlvpn

UnitedStates	Mollisols	Ustolls	Vermiustolls	Vermic Chernozems	CHvm
UnitedStates	Mollisols	Xerolls	Argixerolls	Luvic Kastanozems	KSlv
UnitedStates	Mollisols	Xerolls	Calcixerolls	Calcic Kastanozems	KScc
UnitedStates	Mollisols	Xerolls	Durixerolls	Duric Kastanozems	KSdu
UnitedStates	Mollisols	Xerolls	Haploxerolls	Kastanozems	KS
UnitedStates	Mollisols	Xerolls	Natrixerolls	Mollic Solonetz	SNmo
UnitedStates	Mollisols	Xerolls	Palexerolls	Profondic Luvic Kastanozems	KSlvpn
UnitedStates	Oxisols	Aquox	Acraquox	Gleyic Geric Ferrasols	FRgrgl
UnitedStates	Oxisols	Aquox	Eutraquox	Eutric Gleyic Ferrasols	FRgleu
UnitedStates	Oxisols	Aquox	Haplaquox	Gleyic Ferrasols	FRgl
UnitedStates	Oxisols	Aquox	Plinthaquox	Plinthosols	PT
UnitedStates	Oxisols	Perox	Acroperox	Geric Ferrasols	FRgr
UnitedStates	Oxisols	Perox	Eutroperox	Eutric Ferrasols	FReu
UnitedStates	Oxisols	Perox	Haploperox	Ferrasols	FR
UnitedStates	Oxisols	Perox	Kandiperox	Acric Ferrasols	FRac
UnitedStates	Oxisols	Perox	Sombriperox	Sombric Ferrasols	FRsb
UnitedStates	Oxisols	Torrox	Acrotorrox	Geric Ferrasols	FRgr
UnitedStates	Oxisols	Torrox	Eutrotorrox	Eutric Ferrasols	FReu
UnitedStates	Oxisols	Torrox	Haplotorrox	Ferrasols	FR
UnitedStates	Oxisols	Udox	Acrudoxes	Geric Ferrasols	FRgr
UnitedStates	Oxisols	Udox	Eutrudox	Eutric Ferrasols	FReu
UnitedStates	Oxisols	Udox	Hapludoxes	Ferrasols	FR
UnitedStates	Oxisols	Udox	Kandiudox	Acric Ferrasols	FRac
UnitedStates	Oxisols	Udox	Sombriudox	Sombric Ferrasols	FRsb
UnitedStates	Oxisols	Ustox	Acrustox	Geric Ferrasols	FRgr
UnitedStates	Oxisols	Ustox	Eutrustox	Eutric Ferrasols	FReu
UnitedStates	Oxisols	Ustox	Haplustox	Ferrasols	FR
UnitedStates	Oxisols	Ustox	Kandiustox	Acric Ferrasols	FRac
UnitedStates	Oxisols	Ustox	Sombriustox	Sombric Ferrasols	FRsb

UnitedStates	Spodosols	Aquods	Alaquods	Gleyic Podzols	PZgl
UnitedStates	Spodosols	Aquods	Cryaquods	Gleyic Podzols	PZgl
UnitedStates	Spodosols	Aquods	Duraquods	Densic Gleyic Podzols	PZgldn
UnitedStates	Spodosols	Aquods	Endoaquods	Gleyic Podzols	PZgl
UnitedStates	Spodosols	Aquods	Epiaquods	Stagnic Podzols	PZst
UnitedStates	Spodosols	Aquods	Fragiaquods	Fragic Gleyic Podzols	PZglfg
UnitedStates	Spodosols	Aquods	Haplaquods	Gleyic Podzols	PZgl
UnitedStates	Spodosols	Aquods	Placaquods	Gleyic Placic Podzols	PZpigl
UnitedStates	Spodosols	Cryods	Duricryods	Densic Podzols	PZdn
UnitedStates	Spodosols	Cryods	Haplocryods	Podzols	PZ
UnitedStates	Spodosols	Cryods	Humicryods	Carbic Podzols	PZcb
UnitedStates	Spodosols	Cryods	Placocryods	Placic Podzols	PZpi
UnitedStates	Spodosols	Gelods	Haplogelods	Gelic Podzols	PZge
UnitedStates	Spodosols	Humods	Durihumods	Densic Carbic Podzols	PZcbdn
UnitedStates	Spodosols	Humods	Fragihumods	Fragic Carbic Podzols	PZcbfg
UnitedStates	Spodosols	Humods	Haplohumods	Carbic Podzols	PZcb
UnitedStates	Spodosols	Humods	Placohumods	Placic Carbic Podzols	PZcbpi
UnitedStates	Spodosols	Orthods	Alorthods	Haplic Podzols	PZha
UnitedStates	Spodosols	Orthods	Cryorthods	Solonchaks	SC
UnitedStates	Spodosols	Orthods	Durorthods	Densic Podzols	PZdn
UnitedStates	Spodosols	Orthods	Fragiorthods	Fragic Podzols	PZfg
UnitedStates	Spodosols	Orthods	Haplorthods	Podzols	PZ
UnitedStates	Spodosols	Orthods	Placorthods	Placic Podzols	PZpi
UnitedStates	Ultisols	Aquults	Albaquults	Alic Planosols	PLal
UnitedStates	Ultisols	Aquults	Endoaquults	Gleyic Alisols	ALgl
UnitedStates	Ultisols	Aquults	Epiaquults	Stagnic Alisols	ALst
UnitedStates	Ultisols	Aquults	Fragiaquults	Fragic Gleyic Alisols	ALglfg
UnitedStates	Ultisols	Aquults	Kandiaquults	Profondic Gleyic Acrisols	ACglpn
UnitedStates	Ultisols	Aquults	Kanhaplaquults	Gleyic Acrisols	ACgl
UnitedStates	Ultisols	Aquults	Ochraquults	Alic Planosols	PLal

UnitedStates	Ultisols	Aquults	Paleaquults	Profondic Gleyic Alisols	ALglpn
UnitedStates	Ultisols	Aquults	Plinthaquults	Acric Plinthosols	PTac
UnitedStates	Ultisols	Aquults	Umbraquults	Umbric Gleyic Alisols	ALglum
UnitedStates	Ultisols	Humults	Haplohumults	Alisols	AL
UnitedStates	Ultisols	Humults	Kandihumults	Profondic Acrisols	ACpn
UnitedStates	Ultisols	Humults	Kanhaplohumults	Acrisols	AC
UnitedStates	Ultisols	Humults	Palehumults	Profondic Alisols	ALpn
UnitedStates	Ultisols	Humults	Plinthohumults	Acric Plinthosols	PTac
UnitedStates	Ultisols	Humults	Sombrihumults	Sombric Acrisols	ACsb
UnitedStates	Ultisols	Humults	Tropohumults	Humic Alisols	ALhu
UnitedStates	Ultisols	Udults	Fragiudults	Fragic Alisols	ALfg
UnitedStates	Ultisols	Udults	Hapludults	Alisols	AL
UnitedStates	Ultisols	Udults	Kandiudults	Profondic Acrisols	ACpn
UnitedStates	Ultisols	Udults	Kanhapludults	Acrisols	AC
UnitedStates	Ultisols	Udults	Paleudults	Profondic Alisols	ALpn
UnitedStates	Ultisols	Udults	Plinthudults	Acric Plinthosols	PTac
UnitedStates	Ultisols	Udults	Rhodudults	Rhodic Alisols	ALro
UnitedStates	Ultisols	Ustults	Haplustults	Alisols	AL
UnitedStates	Ultisols	Ustults	Kandiustults	Profondic Acrisols	ACpn
UnitedStates	Ultisols	Ustults	Kanhaplustults	Acrisols	AC
UnitedStates	Ultisols	Ustults	Paleustults	Profondic Alisols	ALpn
UnitedStates	Ultisols	Ustults	Plinthustults	Acric Plinthosols	PTac
UnitedStates	Ultisols	Ustults	Rhodustults	Rhodic Alisols	ALro
UnitedStates	Ultisols	Xerults	Haploxerults	Alisols	AL
UnitedStates	Ultisols	Xerults	Palexerults	Profondic Alisols	ALpn
UnitedStates	Vertisols	Aquerts	Calcaquerts	Calcic Gleyic Vertisols	VRglcc
UnitedStates	Vertisols	Aquerts	Duraquerts	Petroduric Gleyic Vertisols	VRglpd
UnitedStates	Vertisols	Aquerts	Dystraquerts	Dystric Gleyic Vertisols	VRgldy
UnitedStates	Vertisols	Aquerts	Endoaquerts	Gleyic Vertisols	VRgl
UnitedStates	Vertisols	Aquerts	Epiaquerts	Stagnic Vertisols	VRst

UnitedStates	Vertisols	Aquerts	Haplaquolls??	Gleyic Vertisols	VRgl
UnitedStates	Vertisols	Aquerts	Natraquerts	Sodic Gleyic Vertisols	VRglso
UnitedStates	Vertisols	Aquerts	Salaquerts	Gleyic Salic Vertisols	VRszgl
UnitedStates	Vertisols	Cryerts	Haplocryerts	Vertisols	VR
UnitedStates	Vertisols	Cryerts	Humicryerts	Humic Vertisols	VRhu
UnitedStates	Vertisols	Torrerts	Calcitorrerts	Calcic Vertisols	VRcc
UnitedStates	Vertisols	Torrerts	Gypsitorrerts	Gypsic Vertisols	VRgy
UnitedStates	Vertisols	Torrerts	Haplotorrerts	Vertisols	VR
UnitedStates	Vertisols	Torrerts	Salitorrerts	Salic Vertisols	VRsz
UnitedStates	Vertisols	Torrerts	Torrerts	Vertisols	VR
UnitedStates	Vertisols	Uderts	Chromuderts	Vertisols	VR
UnitedStates	Vertisols	Uderts	Dystruderts	Dystric Vertisols	VRdy
UnitedStates	Vertisols	Uderts	Hapluderts	Haplic Vertisols	VRha
UnitedStates	Vertisols	Uderts	Pelluderts	Vertisols	VR
UnitedStates	Vertisols	Usterts	Calciusterts	Calcic Vertisols	VRcc
UnitedStates	Vertisols	Usterts	Chromusterts	Vertisols	VR
UnitedStates	Vertisols	Usterts	Dystrusterts	Dystric Vertisols	VRdy
UnitedStates	Vertisols	Usterts	Gypsusterts	Gypsic Vertisols	VRgy
UnitedStates	Vertisols	Usterts	Haplusterts	Vertisols	VR
UnitedStates	Vertisols	Usterts	Pellusterts	Vertisols	VR
UnitedStates	Vertisols	Usterts	Salusterts	Salic Vertisols	VRsz
UnitedStates	Vertisols	Xererts	Calcixererts	Calcic Vertisols	VRcc
UnitedStates	Vertisols	Xererts	Chromoxererts	Vertisols	VR
UnitedStates	Vertisols	Xererts	Durixererts	Petroduric Vertisols	VRpd
UnitedStates	Vertisols	Xererts	Haploxererts	Vertisols	VR