West African Drylands Project

An Ecosystem Approach to Restoring West African Drylands and Improving Livelihoods through Agroforestry-based Land Management Interventions.

A United Nations Environment Programme (UNEP) project conducted in partnership with the World Agroforestry Centre (ICRAF), the Centre for Environmental Policy of the University of Florida, and the Governments of Burkina Faso, Mali, Mauritania, Niger and Senegal. The project is funded by the Government of Norway.

Training module created by Thomas Gumbricht, www.mapjourney.com

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LESSON 6 – Rain Normalized NDVI

Lesson overview

In this lesson you will learn about how to disentangle rainfall driven vegetation changes from other factors affecting vegetation changes using the concept of Rain Normalized NDVI (RNNDVI); more advanced grid calculation are introduced; you will also learn about using multiple criteria for evaluating land degradation.

Rain Normalized NDVI (RNNDVI)

To overcome the shortcomings of using annual vegetation indexes for tracking land degradation (as in lesson 5), the concept of Rain Use Efficiency (RUE), which combines rainfall and vegetation information, was developed for arid and semi-arid regions. It is an attractive index in regions where growth is limited by rainfall, and where there is a linear relation between rainfall and vegetation. RUE is reported to be lower in degraded arid lands compared to equivalent non-degraded areas and is hence a useful index for separating the effects of rainfall from human factors on temporal changes of vegetation in rangeland ecosystems. As RUE is calculated using seasonal or annual time-steps it is also hypothesized to bridge short-term fluctuations in vegetation dynamics. It, however also means that RUE is not sensitive to short-term droughts or heavy storms, and thus might be biased by such events. The concept of Rain Use Efficiency was developed for estimating Net Primary Production in dryland ecosystems. The West African Drylands project focuses on identifying areas with potential soil degradation (or soil improvements). We do not use the ratio between vegetation and rainfall for primarily forecasting vegetation growth. As we use the ratio between vegetation growth and rainfall as an index for studying changes and trends in time we prefer the term Rain Normalized (RNNDVI) instead of Rain Use Efficiency.

Start a new DIVA-GIS project

Start DIVA-GIS and create a new empty project, save it in your my diva folder, in the tutorial the project is saved as lesson6.div. Add some framework data to use as positional reference (e.g. the national borders and rivers that you used in the previous lessons).

Rainfall grid data

Rainfall grid from 1930 to 2006 are included in the Sahel dataset. The monthly rainfall grid maps from 1930 to 1995 were created by geostatistical interpolation of ground measured rainfall data from gauging stations. The interpolation was done using monthly time steps. Rainfall estimates for the period June 1995 to 2006 were taken from the Africa Data Dissemination Site (ADDS) web page, part of the Famine Early Warning System (FEWS). The FEWS-ADDS rainfall dataset is created from a combination of ground station data and satellite images measuring the cloud temperature, which falls when precipitation is generated from the cloud. The data is originally recorded for 30 minutes and aggregated into daily and 10-day (dekad) datasets. The dataset for the West African Drylands project contains the 10day dataset. Both rainfall datasets were used to calculate the total annual rainfall for each year 1930 to 2006. All the rainfall grid maps are at 8 by 8 km resolution, cut to exactly fit the soil adjusted Normalised Difference Vegetation Index (*NDVI) data introduced in lesson 5. The gridded rainfall datasets included on the project CD are summarized in the table below:

| Dataset	Folder	File
Interpolated rainfall 1930-1995 (monthly)	\data_spatial\sahel\grid\precip\month\YYYY	sahel_precip_YYYY-MM
Satellite supported rainfall 1996-2006 (10day)	\data_spatial\sahel\grid\precip\10day\YYYY	sahel_precip_YYYY-MM-DD
Annual rainfall 1930 – 2006 (combined sources)	\data_spatial\sahel\grid\precip\year\sum	sahel_precip-sum_YYYY

Annual rainfall cycles

Add two or more of the original rainfall layers (monthly data for the period 1930 to 1995, 10day data for the period 1996-2006), representing both the rainy season (May-October) and the dry period. You can choose any year. Below you can see the rainfall over West Africa in July (wet) and November (dry) for the relative wet year 1953. The relative smoothness of the rainfall spatial distribution is an effect of the interpolation technique (variogram fitted kriging) used for creating these grid maps.
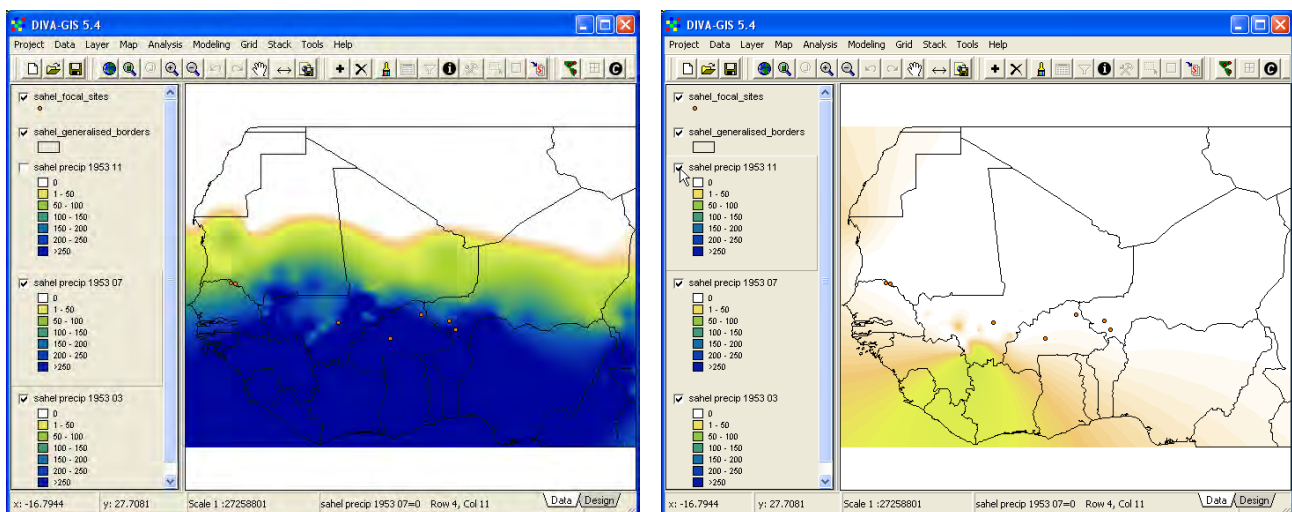

For each annual cycle of rainfall there is a pre-made stack available for plotting the annual rainfall cycle for any year 1930-2006 for any place in West Africa. The plots below show the annual

rainfall cycle for Segou (sentinel site in Mali) for 1953 (wet year during the rainy period in the 1950s and early 1960s), 1984 (at the peak of the droughts during the 1970s and 1980s) and 1994 (with the highest rainfall in the whole period 1930-2006). Note the small initial rainfall peak in the 1994 plot, this is a a typical "mango"-rain, causing vegetation to start growing pre-maturely and then wilting before the normal rainy seasons starts around May. Note how the Y-axis values differ between the plots

| 1953 | 1984 | 1994 |
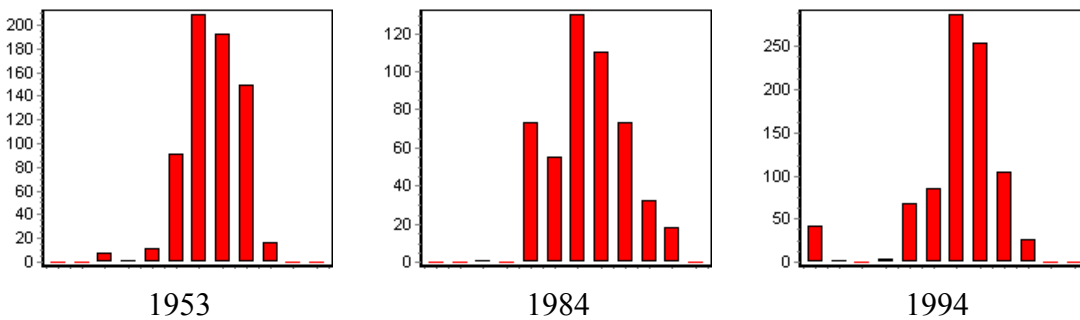
If you look at some of the later years (1996 to 2006 are under the folder \data_spatial\sahel\grid\precip\10day) you can see that the rainfall spatial pattern is more scattered. This is because rainfall for the latter period is estimated based on a combination of rainfall station data and satellite recordings of cloud temperature. In the example below you can see the satellite supported rainfall estimates for the first 10 days of January and the 11-20 of august for the year 2004.
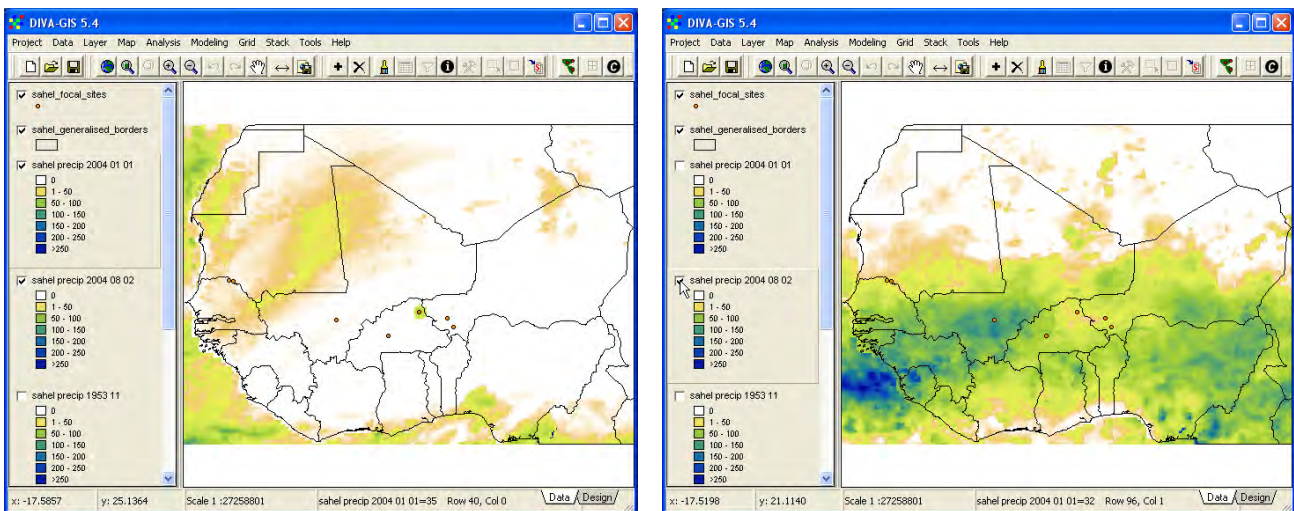

For the years 1996-2006 there are 36 data points representing each annual cycle. As the timesteps are shorter, also the values are lower. The examples below show the plots of the annual cycles for 2001, 2004 and 2006 at the sentinel site in Mali (Segou). Again note how the vertical Y-axis represent different values in the three plots.


| 2001 | 2004 | 2006 |
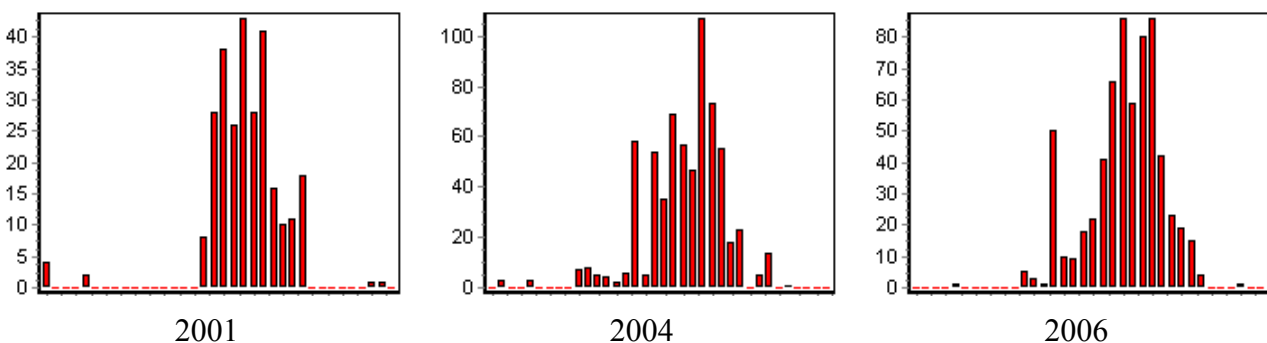
Annual rainfall grid maps

The annual rainfall maps are under the folder \data_spatial\sahel\grid\precip\year\sum, add two or more of the annual rainfall maps to you DIVA-GIS project. Below are the annual rainfall maps for 1984 (dry) and 2004 ("normal"). The difference in creating the maps can be seen, with the 1984 map being smoother and not recognizing the coast line (all rainfall stations used in the interpolation are continental).
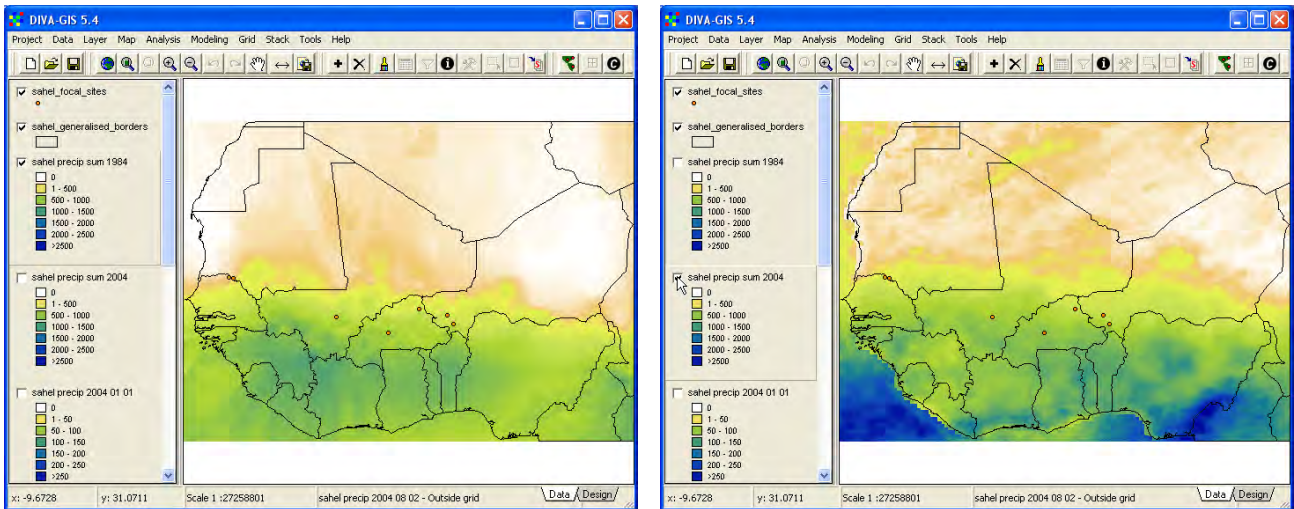
There are two stacks available in the folder with the annual rainfall maps – one for the whole data period (1930-2006) and one for the period coinciding with the vegetation data you used in lesson 5 (1982-2006). Use the Stack Plot tool to look at the rainfall variation over the periods 1930-2006 and 1982-2006. The stack plots below show rainfall and vegetation production (annual increment *NDVI) for the sentinel site in Mali (Segou) 1982 to 2006. There is an upward trend in both rainfall and vegetation production for this site over this time period.
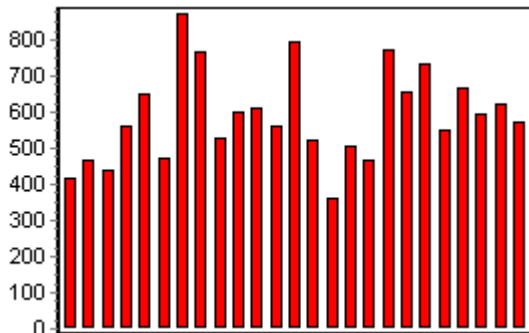
Annual rainfall (mm) at Segou (Mali) 1982-2006
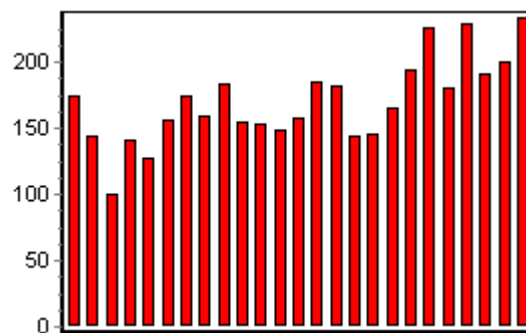
*Annual vegetation production (increment *NDVI) at Segou (Mali) 1982-2006*

You can use DIVA-GIS to do various interesting calculations and analysis using the rainfall and vegetation data available in the project dataset. In lessons 4 and 5 you used visual exploration of the relations between vegetation growth on one hand and protected area and topography (river basins and rivers) on the other. You also made a regression to study temporal changes using a stack with time-series data as input.

Annual rainfall isohyet vector maps

The annual rainfall can also be mapped as isohyets – lines showing positions of equal rainfall. In the dataset there is a shape layer containing all the 100 mm isohyets for 100 mm -900 mm of annual rainfall for each year 1930 to 2006, under \data_spatial\sahel\mapdata\climate\ sahel_isohyets_1930-2006.shp. Add this file to your DIVA-GIS project. If you turn it on, you will just see a map loaded with spaghetti – it is impossible to make anything out. The best option now is to use the Filter tool, [image], (also available via the menu: Layer – Filter). Make sure the layer with all

the isohyets is the active theme and open the Filter window. In the Filter window you have three tabs – Single Value, Multiple Values and Annotate. For now you can use the Single Value tab. Select Field to be YEAR and Value to be 1984, as shown below.

DIVA-GIS will filter the isohyets and only show the isohyets for 1984 in the Data view and the Legend (as shown in the image below).

If you now turn on the rainfall grid layer that represent the same year as the isohyets in the View, you should see how the isohyets vector lines are aligned with cells of similar value in the grid map. You can test this by making both the isohyet layer and the corresponding grid layer active (see lesson 2 to repeat making two or more layers active), and then use the Identify feature tool. In the example below you can see how the grid value under the 300 mm isohyet at the indicated point is close to 300. You can also symbolize the rainfall grid layer to more clearly show the isohyets.
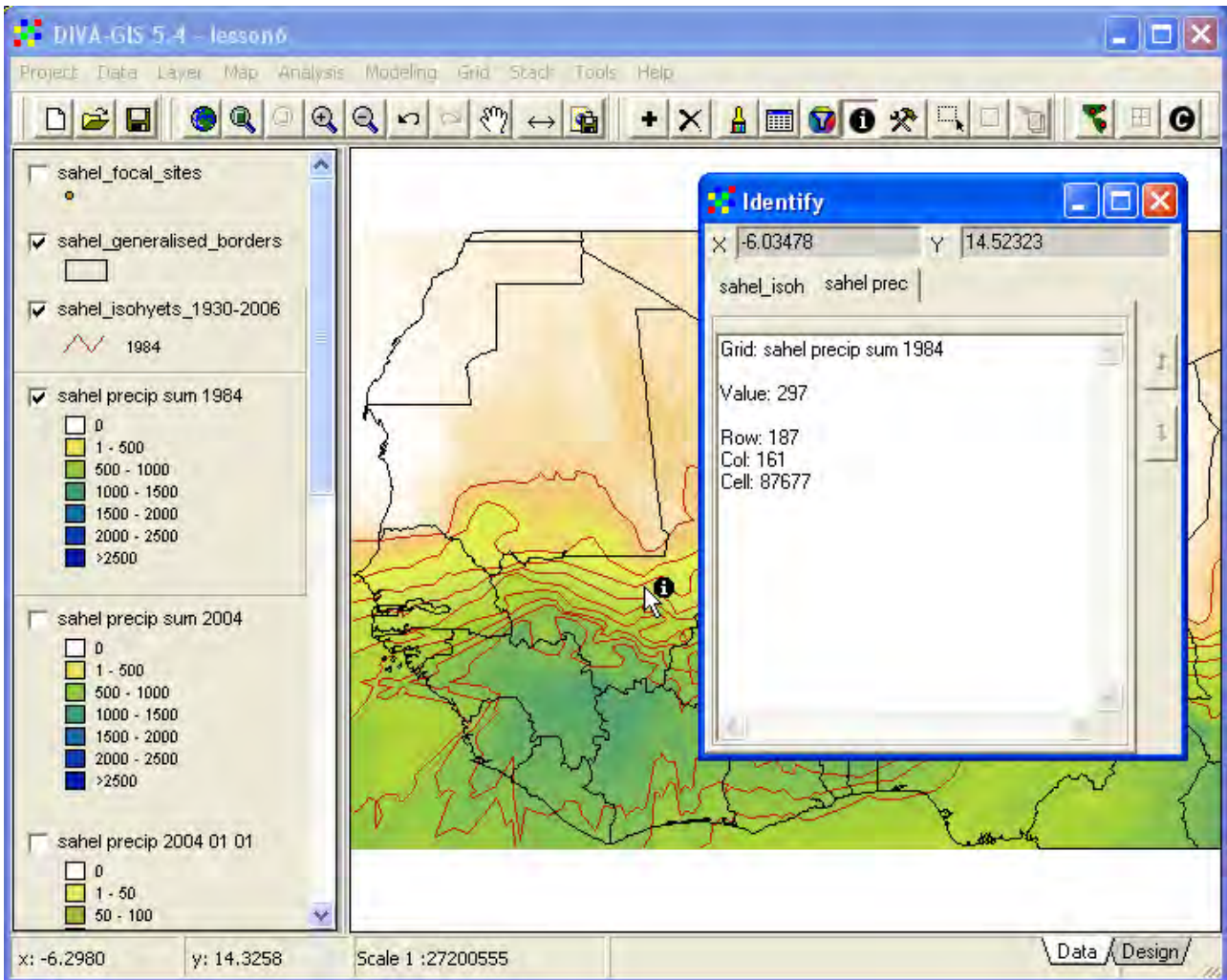
You can also use the Query tool to select the isohyets you are interested in, and then save the selection to a separate shape file (introduced in lesson 2). As an example you can select the isohyets between 300 and 700 mm, representing particular years, or a period of several years.

Make the layer with all the isohyets the active theme, open the Select window (from the menu:

Layer – Select Records, or via the Query tool, ⚒). Use Select by query to construct the following query for selecting isolines between 300 and 700 mm for the years 1984 and 2004 (note that you must have a parenthesis around the OR, otherwise it will not work properly).

(ISOVALUE > 299) AND (ISOVALUE < 701) AND ((YEAR = 1984) OR   (YEAR = 2004))
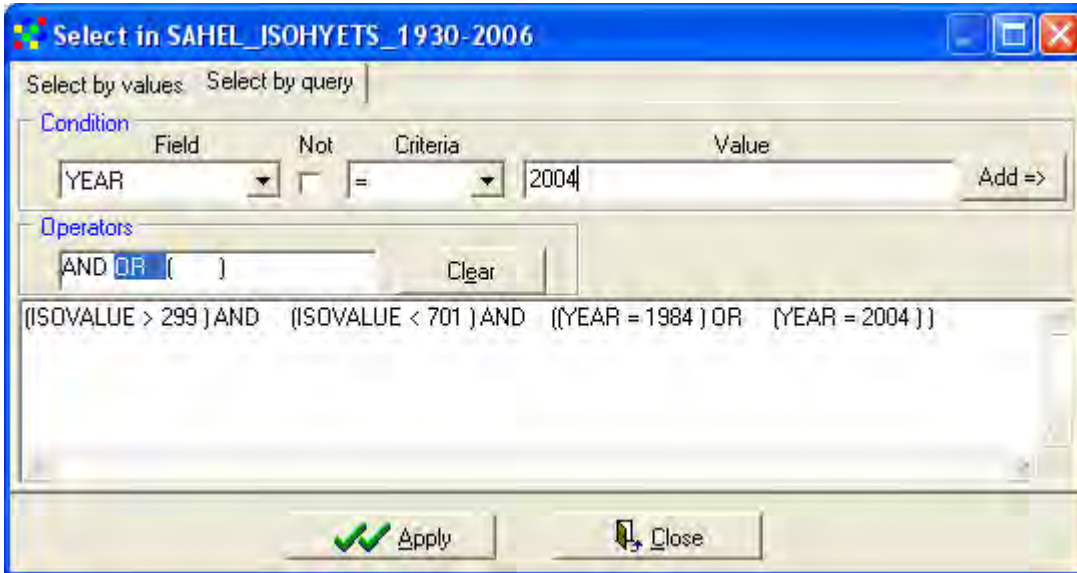
If the query is correct clicking Apply will select the isolines you requested. You can now save the selection to a separate shape file by clicking the Convert to Shapefile tool (or go via the menu: Data – Selection to new Shapefile). Save the new shapefile to you my diva folder. The new shape file will be automatically added to the project window.

Average rainfall isohyets 1930-2006

In the main report the average rainfall for different periods is used to analyze the relationship between average rainfall and RNNDVI variations. The average isohyet positions for these periods are also available in the dataset, as given in the table below.

| Dataset	Folder	File
Average isohyet position 1930-2006	\data_spatial\sahel\mapdata\climate	sahel_isohyets-x_1930-2006
Average isohyet position 1982-2006	\data_spatial\sahel\mapdata\climate	sahel_isohyets-x_1982-2006
Average isohyet position 1982-1987	\data_spatial\sahel\mapdata\climate	sahel_isohyets-x_1982-1987
Average isohyet position 2000-2006	\data_spatial\sahel\mapdata\climate	sahel_isohyets-x_2000-2006

Calculating Rain Normalized NDVI

Rain Normalization of NDVI (RNNDVI) is a method to disentangle the rainfall driven variation in vegetation growth from other factors governing changes in vegetation (see above). RNNDVI is simply calculated as the ratio between an annual vegetation production index and annual rainfall (some studies use growing season instead of annual indexes, but in this project the annual indexes have been used – see lesson 5). As the Sahel dataset contains both annual rainfall and annual vegetation production maps, you can use DIVA-GIS to calculate the annual Rain Normalized NDVI.

From the DIVA-GIS menu choose Grid – Overlay, select the vegetation index as the First grid, and the rainfall as the Second grid, both grids representing the same year. In the example below the increment *NDVI for 2004 is divided with the annual rainfall for 2004. Choose Divide as the Operation, and give a logical Output file name by clicking Result (put the result in your my diva folder, or create a separate folder). Click Apply to run the operation and create a RNNDVI grid.
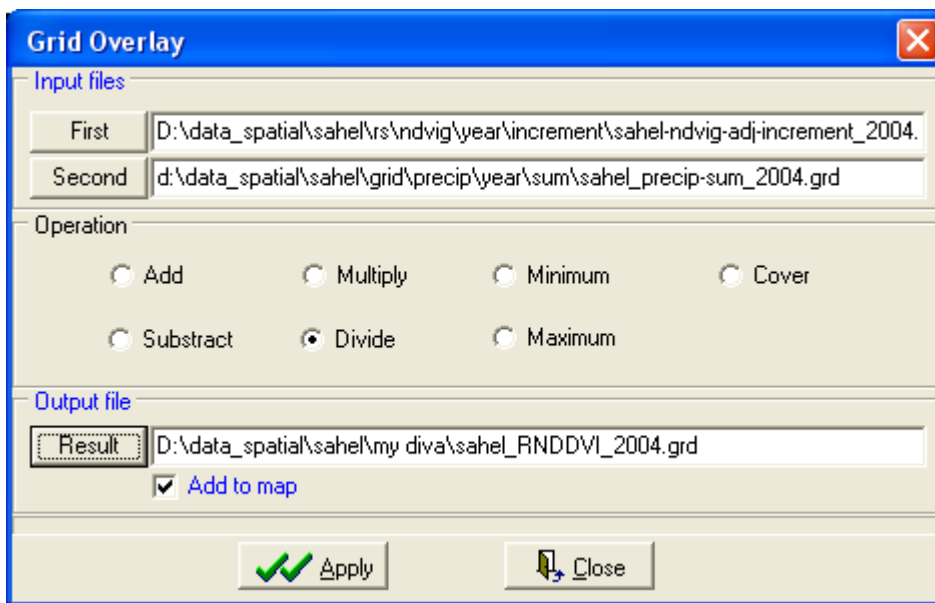

The value of the resulting RNNDVI grid will vary dependent on the data ranges in the year you choose for your calculation, and for some areas you might get a negative RNNDVI (e.g. water areas). RNNDVI in general has values between 0 and 2.5 with the input units used in the dataset. When calculating RNNDVI areas with low rainfall but high vegetation production will generate very high RNNDVI values. This can for instance be irrigated areas, or flooding areas like the Niger inland delta in Mali. DIVA-GIS sets the default legend after the highest and lowest value resulting from the overlay analysis, so by default your RNNDI map will become a (rather) green map. You can check the actual values by either using the Identify tool, 🛈, by making a transect (see lesson 5) or by making a histogram of the calculated RNNDVI map (see lesson 5). Below is the RNNDVI map calculated above, with the identify tool showing the actual RNNDVI value near Segou in Mali.
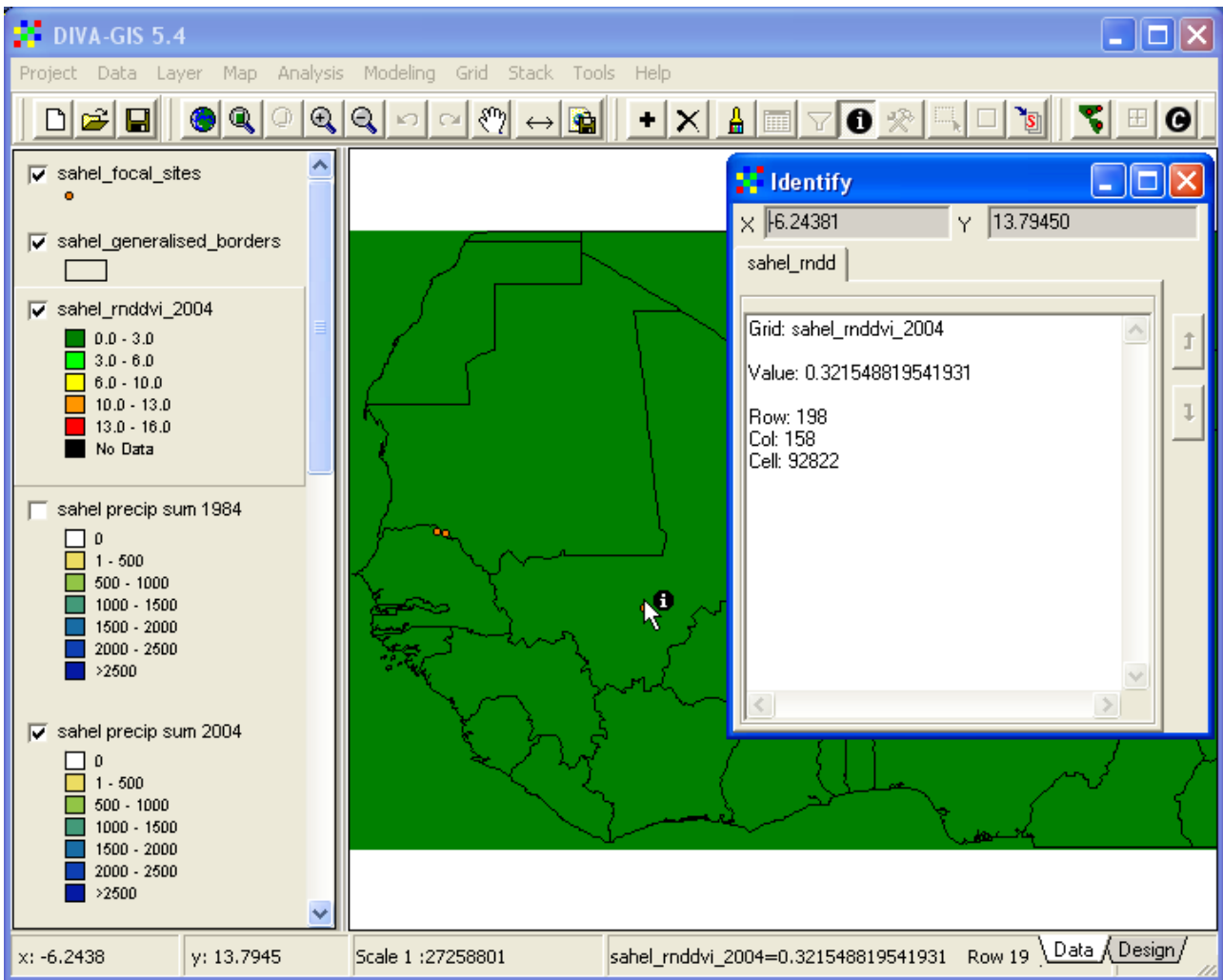
Then the transect through from South to North (same transect as shown in lessons 4 and 5) showing the RNNDV at longitude -4.5.
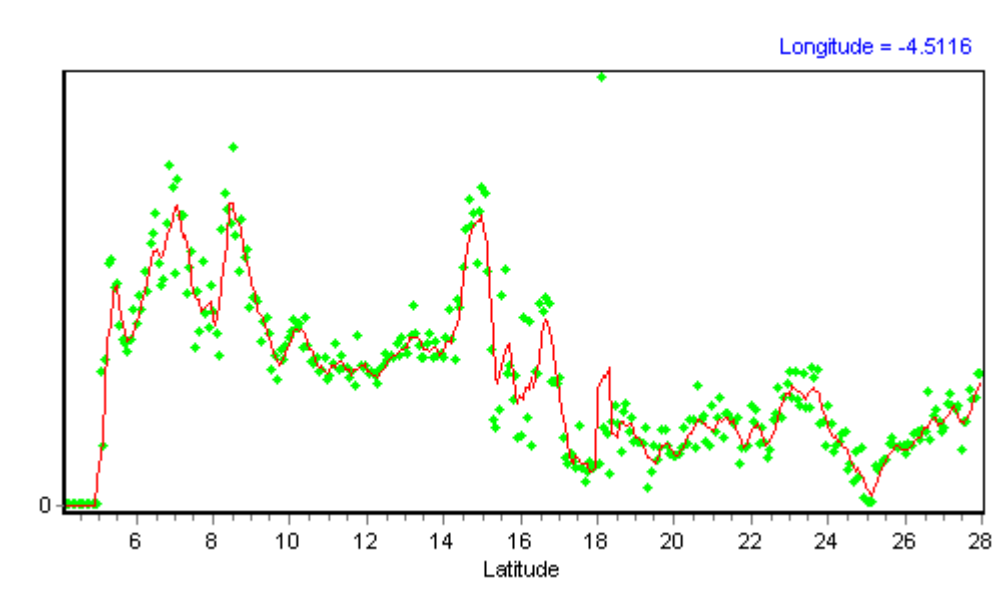

To make a histogram of the calculated RNNDVI grid you must set the histogram options manually, for example as shown below. If you use the default setting of displaying the histogram using the Legend entries, you will again get almost all pixels falling in one class.
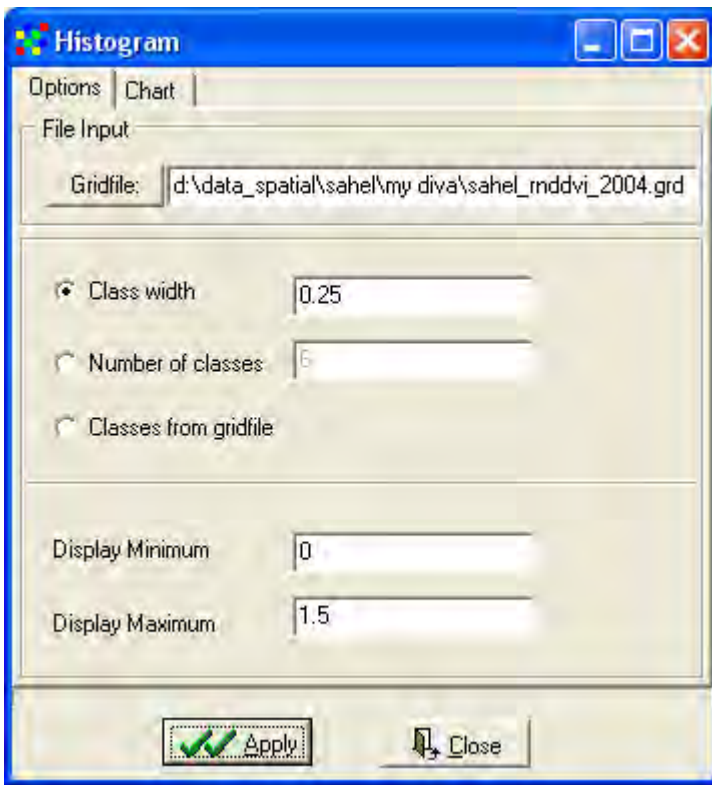
With the manual set Histogram options you see that most RNNDVI values are lower than 1.
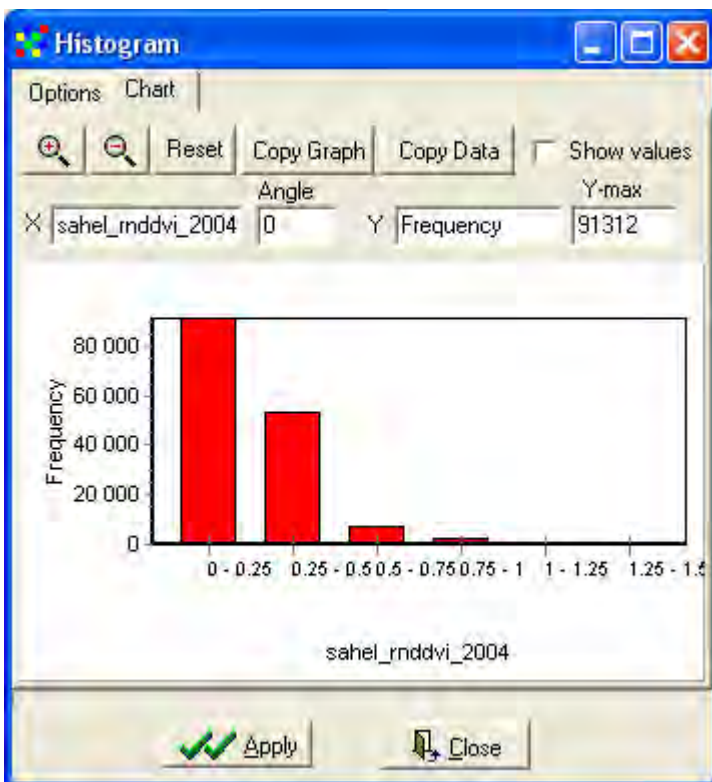
If you look at the histogram above you can get an idea of how to rearrange the legend in order to symbolize the calculated RNNDVI layer. Use this information to set the legend for the RNNDVI layer (the RNNDVI data is of the type ratio, see lesson 4 to repeat symbolization of grid ratio data). From the symbolized RNNDVI example below you can clearly see how some patches get very high values.
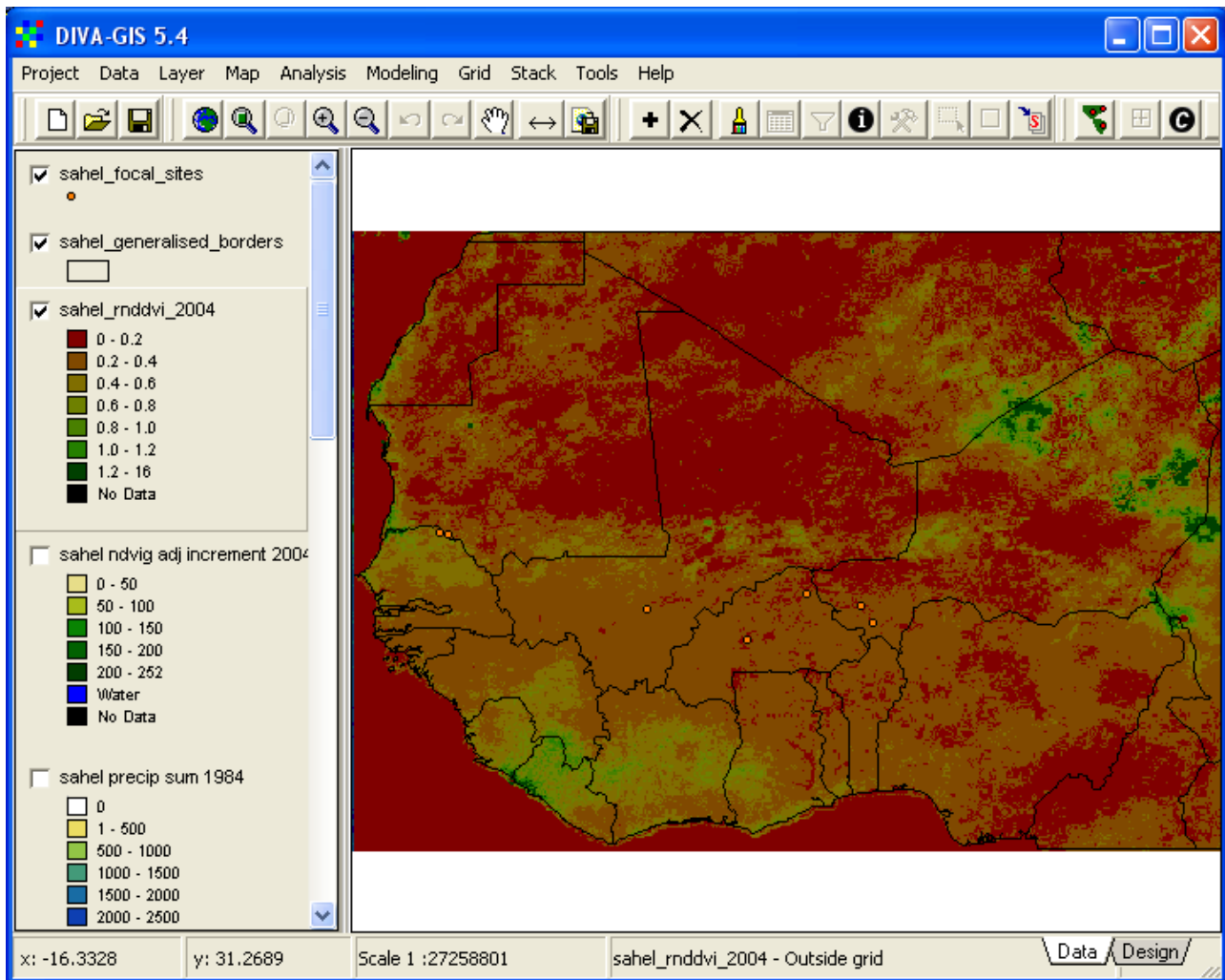
You can analyze the cause of these anomalous areas by adding the vegetation grid you used for the calculation, then make both the vegetation and the rainfall grid used for calculating the RNNDIV active (hold down ctrl+alt and click both layers in the Legend – both will then appear lifted). Choose the Identify tool again, and click in one of the anomalous areas. In the example below a point in Lake Chad was clicked (as indicated) and by comparing the results under both tabs in the Identify window you can see the original values that generated the anomalously high RNNDVI for Lake Chad. If you click to a point next to Lake Chad you will see that rainfall does not change much, but that vegetation production goes down. Lake Chad is fed by water also by runoff and runon, and hence vegetation has other sources of water than rainfall to grow from. The same phenomena occurs around the lower sections of Niger River. The anomalous areas further north in Niger are more difficult to explain. Either it could be the drainage pattern, or irrigation, or an overestimation of *NDVI in dry areas (soil influencing the *NDVI value despite the soil adjustment done as a preprocessing – see lesson 5). Below is the pre-made RNNDVI grid data for the same year that is shown in the image above. The calculation of RNNDVI in the dataset was done setting a threshold on the rainfall - to annual rainfall levels below 25 mm. As you see the anomalous RNNDVI areas in the north of Niger are registered as No Data in the pre-calculated RNNDVI dataset.
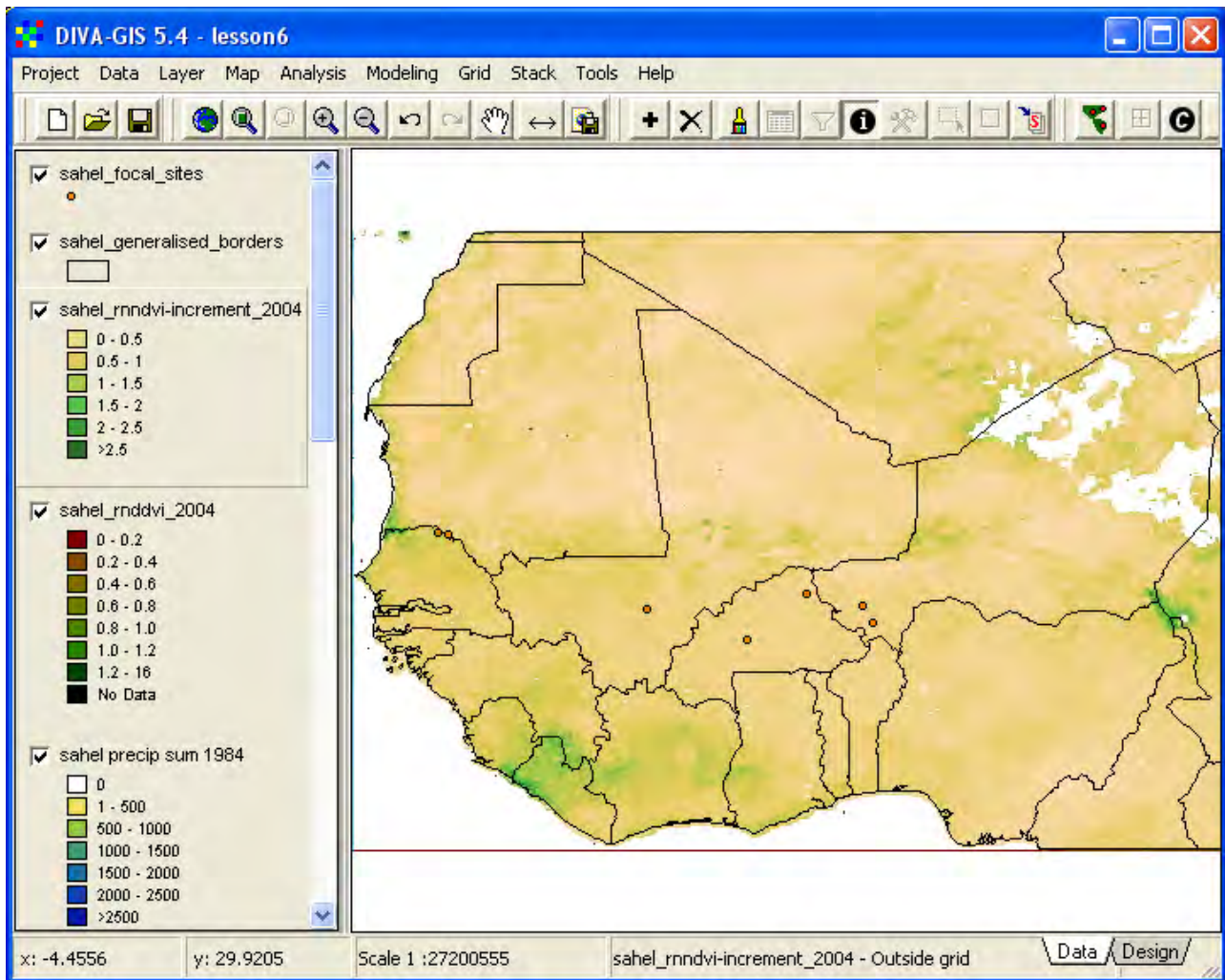
The RNNDVI layer shows the variation in vegetation growth with the influence of rainfall taken away. If the vegetation data had been in units of biomass production per area (e.g. g/m^2), RNNDVI would have shown the absolute growth per mm of rainfall (and hence a proper Rain Use Efficiency - RUE). There are documented methods to convert NDVI to absolute biomass growth, but detailed ground surveys are needed to adopt those methods. And in this study we are mostly interested in finding areas that have relatively higher and lower RNNDVI and areas where RNNDVI has changed over time, hence the indexed RNNDVI that you just calculated will be sufficient.

The RNNDVI for West Africa is already calculated for each year 1982 to 2006, with annual vegetation production indexed using annual average *NDVI, annual maximum *NDIV and annual increment *NDVI (see lesson 5). The table below shows where to find the different datasets.

Annual RNNDVI index	Folder
Annual average *NDVI / rainfall	\data_spatial\sahel\rs\rnndvi\year\average
Annual maximum *NDVI / rainfall	\data_spatial\sahel\rs\rnndvi\year\max
Annual increment *NDVI / rainfall	\data_spatial\sahel\rs\rnndvi\year\increment

For each index there are layers representing the mean situation for the period 1982-2006, the normalized trend slope 1982-2006 based on z-scores (see lesson 5 to repeat normalization and z-scores), the normalized trend slope coefficient of determination (regression r2) 1982-2006, and layers showing the significance (p) of positive and negative trends. The significance was calculated by comparing the actual trend with 999 random trends (permutations). These layers are named

according to the table below (where "index" should be exchanged for "average", "max" and "increment" respectively).

Layer	Layer name
Mean 1982-2006	sahel_rnndvi-"index"-x_1982-2006
Normalized trend slope 1982-2006	sahel_rnndvi-"index"-z-slope_1982-2006
Correlation of normalized trend slope 1982-2006	sahel_rnndvi-"index"-z-r2_1982-2006
Significance of positive normalized trend	sahel_rnndvi-"index"-z-pos-p_1982-2006
Significance of negative normalized trend	sahel_rnndvi-"index"-z-neg-p_1982-2006

For each index there is also a pre-built stack available. You can use the stack for doing your own trend calculations using the original (rather than normalized) data. The stack can also be used to finding overall minimum or maximum RNNDVI for any pixel in the data, or for calculating averages. If you want to analyze a shorter period than 1982-2006 you can edit the existing stack, or build a new stack – both options available under the menu: Stack – Make Stack (see lesson 4 to repeat building a stack).

RNNDVI changes 1982 to 2006

The image below shows the RNNDVI z-score (normalized) trend 1982-2004. Note that the legend has been constructed to show RNNDVI at a logarithmic scale – the underlying data is however linear. Areas with a higher average rainfall than 900 mm has been masked out. This is because at rainfall levels higher than around 900 mm rainfall, vegetation production is not linearly dependent on rainfall (you analyzed the relation between rainfall and vegetation production in lesson 5). To show the 900 mm isohyet (average for the period 1930-2006) you can add the layer with the average isohyet positions (\data_spatial\sahel\mapdata\climate\sahel_isohyets-x_1930-2006) and then use the Filter function to only retain the 900 mm isohyet in the Data view. This is illustrated below.
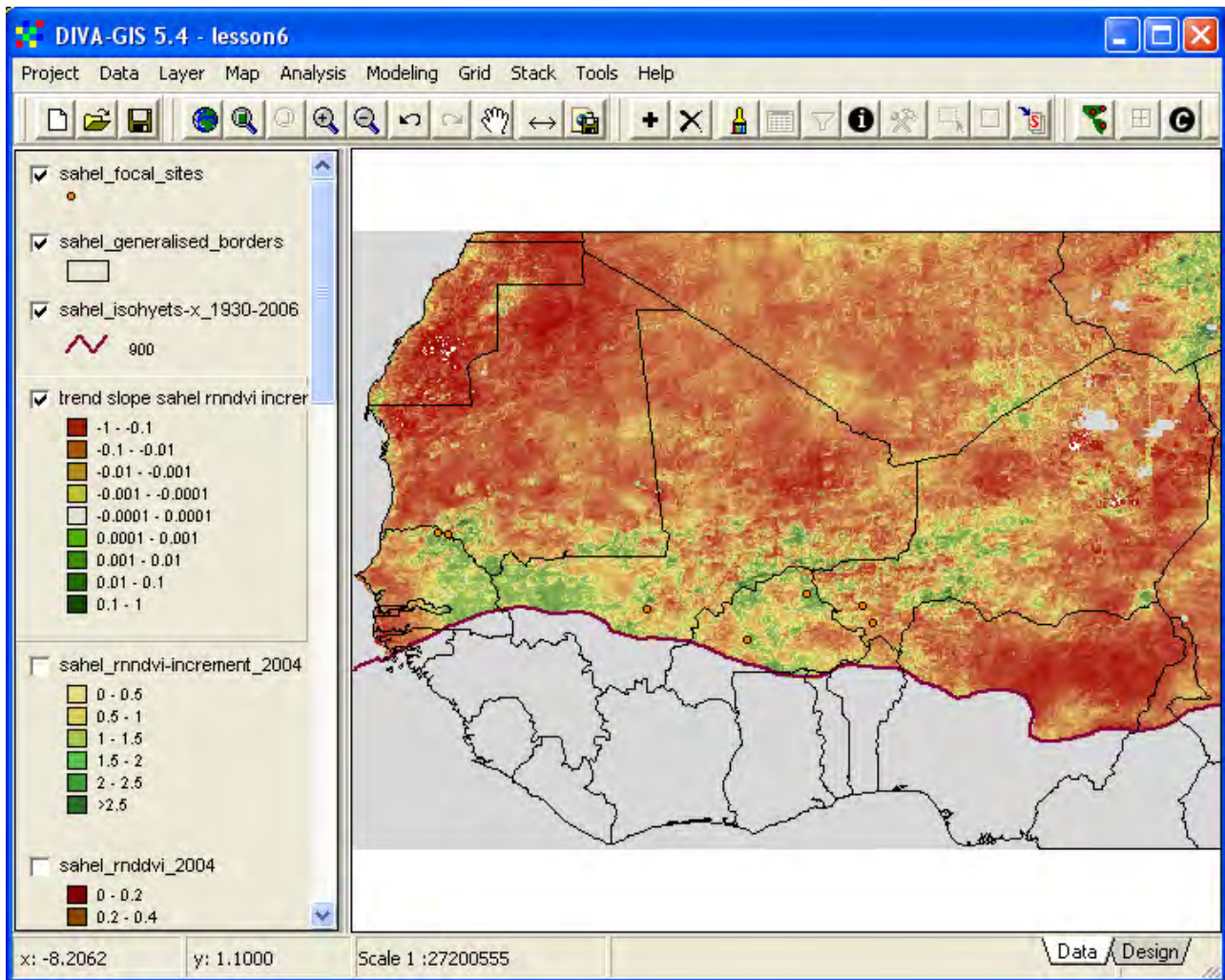
The trend map above is in our view one of the best indicators of land degradation in the medium term (25 years) available for West Africa. There are similar grid maps available also for RNNDVI calculated from the more common vegetation production indexes – annual average *NDVI and annual maximum *NDVI.

Analyzing RNNDVI and rainfall variation

In the main report there is a thorough analysis of the relation between RNNDVI and rainfall spatial and temporal variation (section 6.5). Rain Use Efficiency, or RNNDVI as used in this project, is supposed to be highest around the average rainfall situation for a particular point. Deviation from the average rainfall is hypothesized to decrease RUE or RNNDVI. At lower than average rainfall a larger part of the rainfall will be intercepted and evaporated directly back to the atmosphere, hence being unavailable for vegetation growth. At higher than average rainfall a larger part of the rainfall forms runoff, and also becomes unavailable for plant growth. In general also the vegetation at a particular site should have developed as a response to the average rainfall situation and hence be geared up to perform best at that rainfall level. This hypothesis on the relation between RNNDVI and rainfall variation can be tested using the Sahel dataset.

Doing the analysis involves the following steps:

1. Calculating the average rainfall situation for a particular period (in the main report we used 1982-2006, 1982-1987 and 2000-2006 for representing average, dry and wet periods).

2. Probing the relation between annual RNNDVI and annual rainfall for individual years in the selected period.

3. Plotting the results, and use statistical methods for analyzing variations and trends.

Step 1 and 2 can easily be done using DIVA-GIS, and step 3 can be done in Microsoft excel and other plotting software.

To do step 1 above you must build a stack holding the annual rainfall grids representing you study period, this is done from the menu: Stack – Make stack.
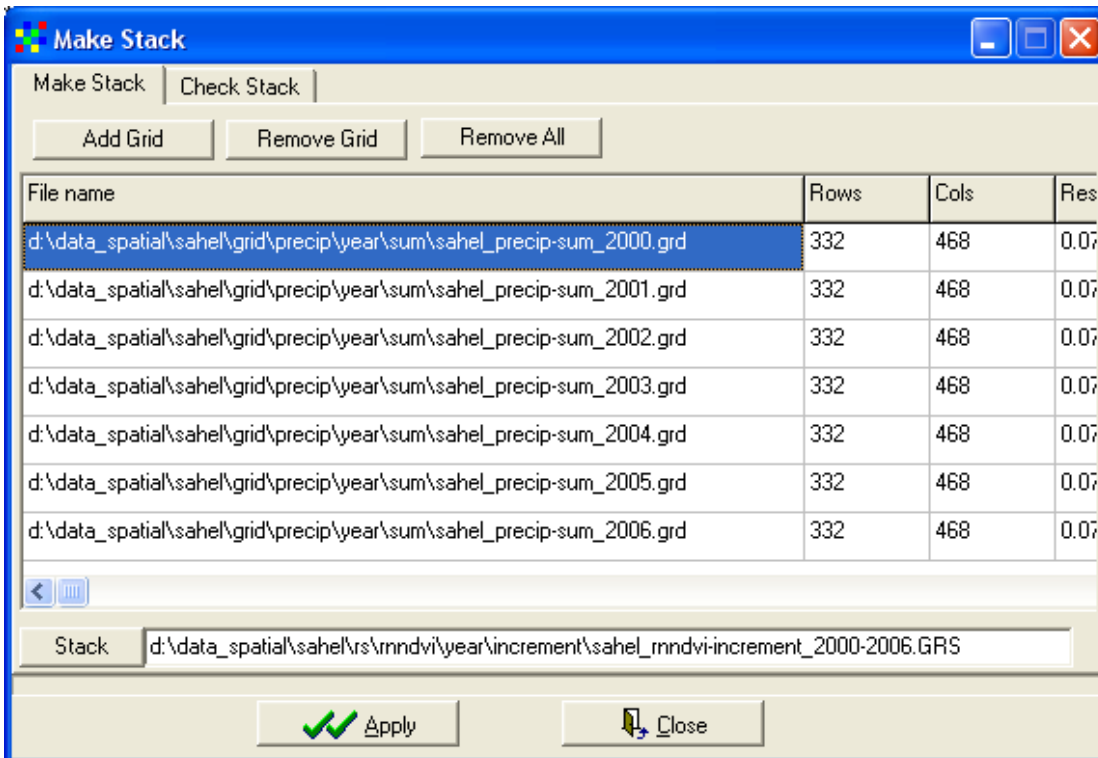
Click Apply to save the stack. You can now use the stack to calculate the average annual rainfall for the period 2000-2006. Go via the menu: Stack – Calculate, as shown below.
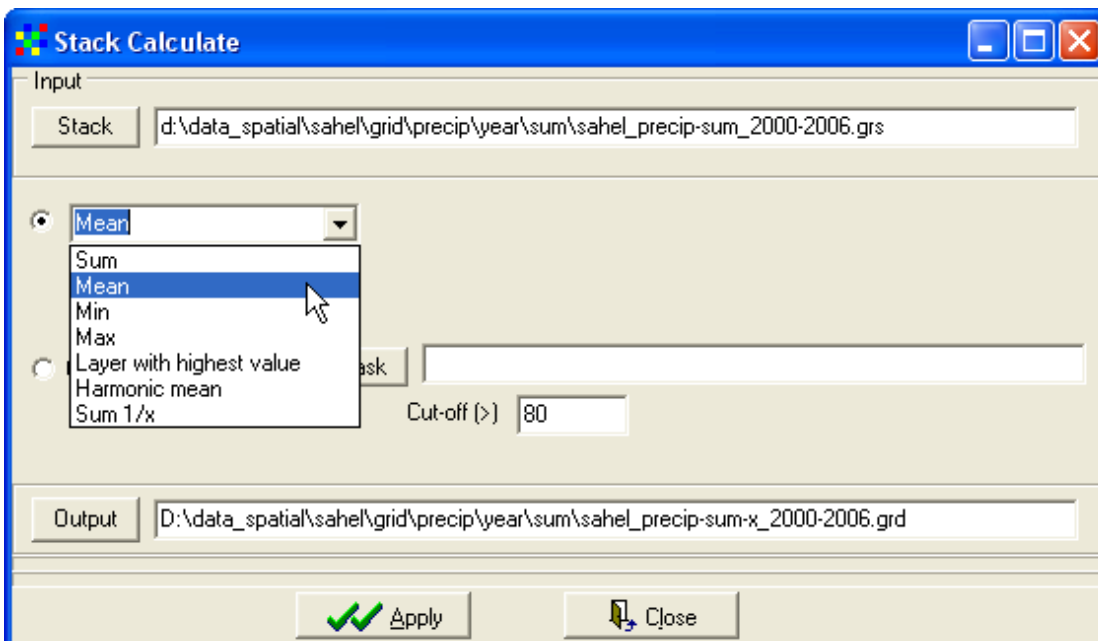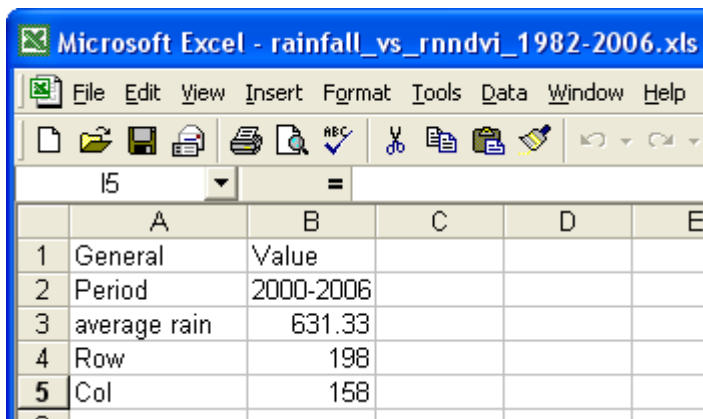

Click Apply to calculate the mean (or average) rainfall for the period represented in the stack (2000-2006).

Build a second stack, but this time with one of the annual RNNDVI grids representing the same period as the rainfall grids. The grids in this second stack must come in the exactly same order as the grids in the rainfall stack.

Decide which position in the map you want to analyze, for instance one of the sentinel sites, or another reference point for which you have information. Make sure the mean rainfall map for your study period (the one created above) is the active layer, and select the Identify tool. Click on the position you want to study. In the Identify window note the information on Value, Row and Col (the mean rainfall, and the point position in grid rows and columns).

Using Microsoft excel together with DIVA-GIS

You now have to use some additional software for storing and analyzing the data you retrieve from DIVA-GIS - in the tutorial Microsoft excel will be used (an alternative is open office calc, that can be downloaded for free from www.openoffice.org, it works very much like excel). Start Microsoft excel and open a new calculation sheet. Enter the values you got manually as shown below.

Open the Stack Plot window (from the menu: Stack – Plot). Load the Stack for rainfall grids that you created above. Manually enter the Row and Column positions you got from the Identify tool (and transferred to the Excel sheet), then click the Apply button in the Stack Plot window.
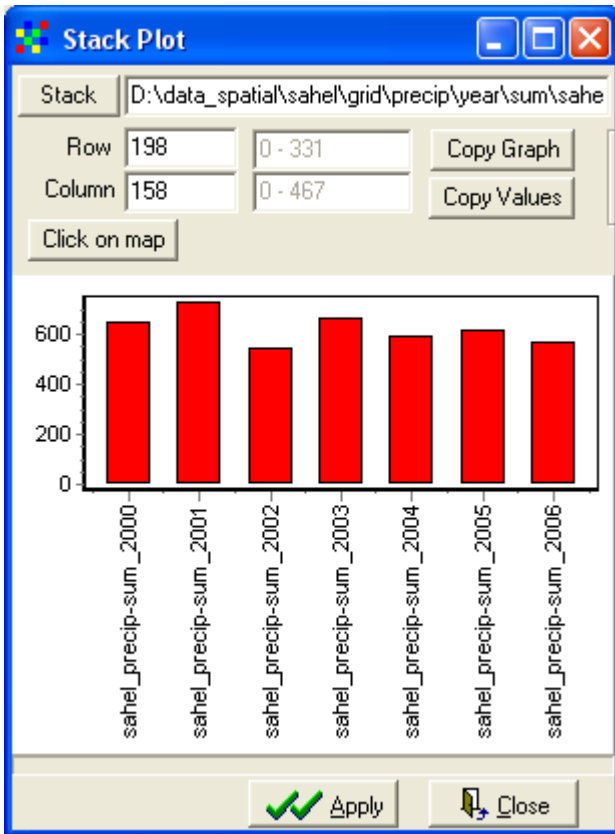
As you see there is a slight variation in rainfall, but not as large as if you had selected the whole study period. To get the values of the rainfall shown in the plot transferred to excel, click the Copy Values button, Copy Values, in the Stack Plot window. Then put the cursor inside the excel sheet, at position C1 as indicated below. Then press ctrl-v (or use the excel menu: Edit – Paste). The rainfall data for your point will now be pasted into excel.

Change Stack to the RNNDVI stack representing the same period, and repeat the steps but paste the RNNDVI at position E1 in the excel sheet. Make sure that the rainfall data and RNNDVI represent the same years by looking in the columns headed Grid in the excel sheet, that should now look like the example below.

Change the titles at D1 and FI to Rainfall and RNNDVI, then click the column D, hold down the Ctrl key and click column F, both columns should now be blueish (as in the image below). Then click the Chart Wizard tool, , in excel.
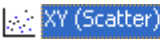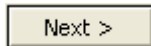

Select XY (scatter), , as the chart type and then click Next, until you get the graph. You can edit the graph layout in excel, but your graph should look similar to the example below.
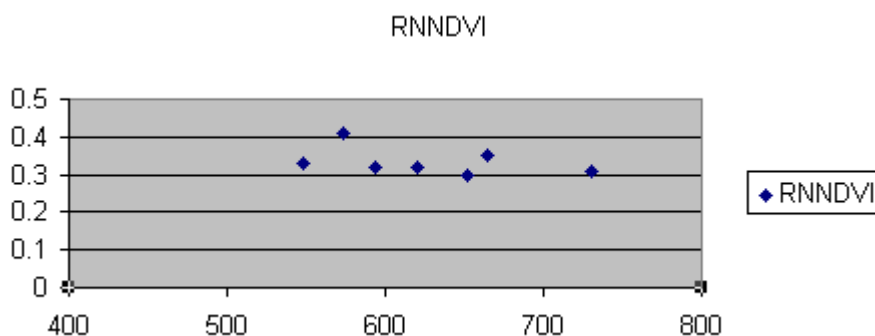
The rainfall is shown along the X-axis, and the RNNDVI on the Y-axis. The increment *RNNDVI for this position (Segou in Mali) does not show any peak around the average rainfall (626 mm) for the period analyzed (2000-2006) as suggested by the RUE hypothesis. This might depend on the close proximity to the Niger River, and you will get different results when using different indexes, different positions and for different periods. The trend you see above, with higher RNNDVI at

lower rainfall for a specific position, is however consistent for the whole dataset (see section 6.5.1 in the main report).

In the main report a more thorough statistical evaluation on the relation between rainfall variation and RNNDVI was done for all indexes (average *NDVI, maximum *NDVI and increment *NDVI). The main report also includes an analysis of how RNNDVI in one year depends on rainfall the previous year. The overall conclusion from these analyses is that the increment index perform superior to the traditional indexes.

Save you DIVA-GIS project, as in the next section you will create a new project.

Spatial ranking of best and worst performing cells

From a technical perspective, all the above vegetation analyses are driven by the AVHRR NDVI data and the results of the trends might be biased because of systematic errors over time. These errors stem from the data being captured by six generations of AVHRR sensors, with each sensor degrading over time, and capturing images at different time of the day (with differences in solar position). Volcanic eruption from Pinatubo in 1994 changed the atmosphere and hence the satellite registration of reflectance. As you have seen above, the rainfall data is also not consistent, and stem from different sources at different times.

In an effort to overcome errors originating in systematic shifts and variations in sensor and atmospheric conditions, a goal driven approach for identifying the best and worst performing areas with regard to both absolute and rain adjusted vegetation growth was developed for the project. Under the assumption that sensor and atmospheric variations would have a consistent spatial influence but vary over time, the vegetation growth for each year in the time-series was spatially ranked from highest to lowest growth to receive yearly maps of relative vegetation performance over a given spatial domain. The change in ranking position for each pixel was then analyzed as a normalized time-trend regression for the period 1982-2006. The resulting map lacks any physical meaning, but the relative vegetation performance of all pixels vis-à-vis each other in the spatial domain used in the analysis can be identified.

This goal-driven ranking approach was applied at two different spatial scales. 1) a regional ranking encompassing the Sahel Parklands (bounded by 11-18°N) where all pixels were compared with each other, and 2) a focal or neighboring ranking where the vegetation growth of each pixel was compared with the growth of its 8 closest neighbors. The analysis was done only for incremental *NDVI (as only relative growth is interesting, all indexes will generate very similar results), and excluded the anomalous areas along the coast and around Lake Chad.

The ranking data for the Parkland is in the dataset, as given in the table below:

| Dataset	Folder
Regional *NDVI ranking	\data_spatial\parklands\rs\ranking\region-NDVI
Regional RNNDVI rakning	\data_spatial\parklands\rs\ranking\region-RNNDVI
Focal *NDVI ranking	\data_spatial\parklands\rs\ranking\focal-NDVI

For each ranking dataset there are annual rankings, annual mean and standard deviation grids available. There is also a normalized trend grid, and grids with the significance of positive and negative trends. Remember that the values in all these grids are just relative and can not be interpreted, the grids are intended for identifying best and worst performing cells over different spatial domains.

Regional ranking of annual vegetation production

Create a new empty DIVA-GIS project (e.g. as lesson6b in your my diva folder, and add an annual *NDVI ranking grid, or the mean *NDVI ranking for the period 1982-2006 (shown below).
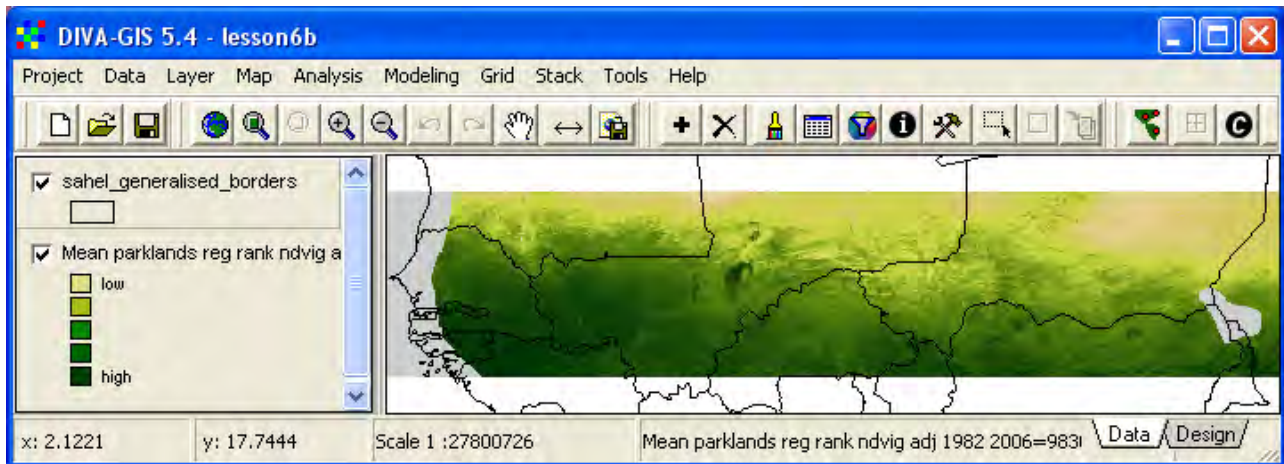
The regional ranking simply shows the brownest to greenest pixel in the analyzed region. The image, however more clearly show anomalous regions, including the Niger inland delta in central Mali compared to the original datasets. One way to use the time series of ranking images is to analyze the variation in relative ranking position for each pixel in the spatial domain of the ranking analysis. The image below (parklands_reg-rank-ndvig-adj-std_1982-2006) shows the variation (standard deviation) of the ranking position of each cell for the period 1982 to 2006. If you are looking for areas that have gone through either smaller or larger changes, this image is a useful starting point.
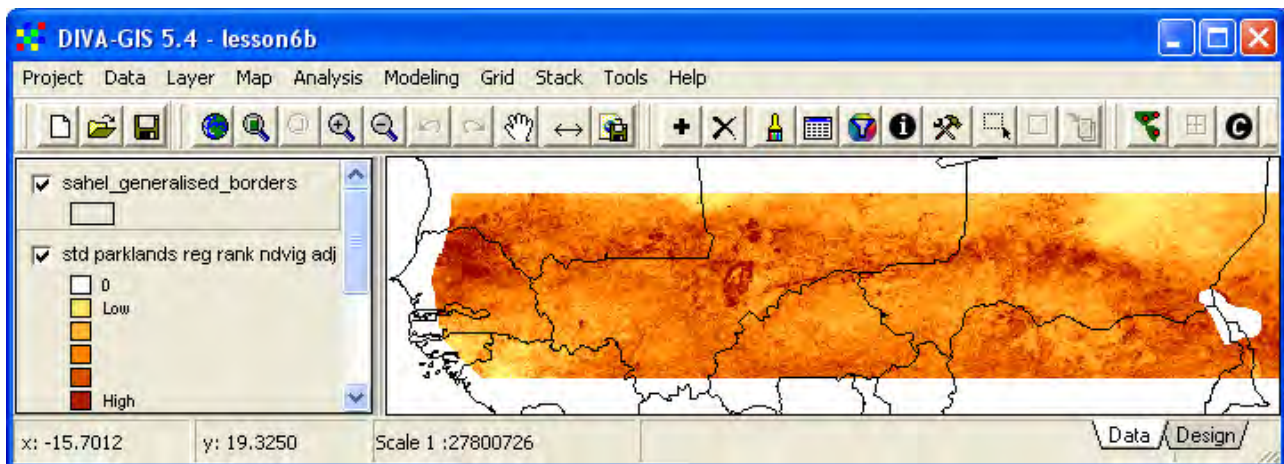

Also the trend slope image for regional ranking position is included in the dataset (parklands_reg-rank-ndvig-adj-z-slope_1982-2006), and shown below.
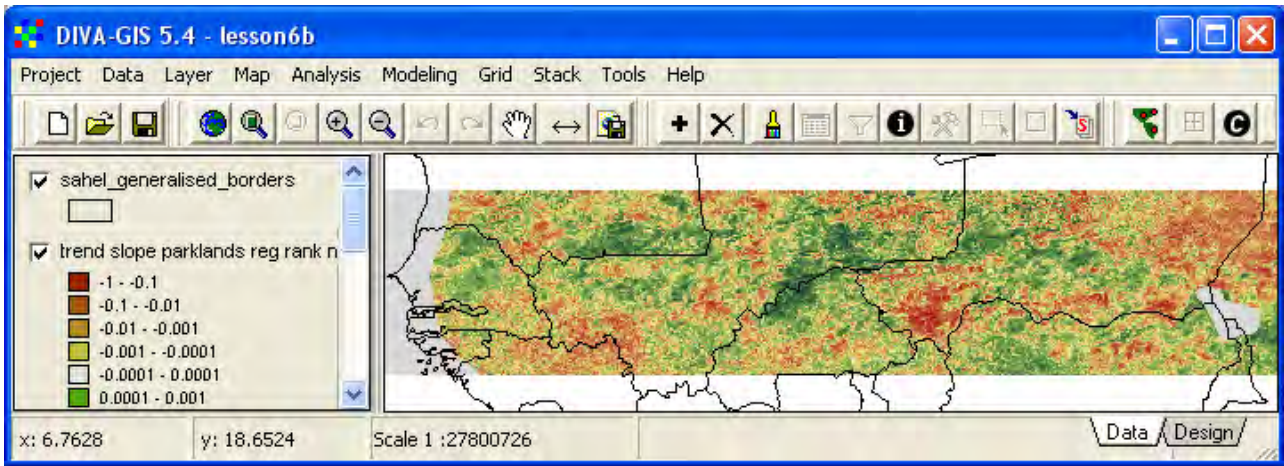
Note that the trend shows changes in relative vegetation production (annual increment *NDVI) and the image can only be used for finding areas performing better or worse, the image does not tell which areas that have actually greened up or browned down. Again the use of the image above is to identify areas which have performed relatively better or worse. For this purpose the images above are better suited than the original images, because the latter are plagued by the inter-annual errors stemming from sensor degradation and atmospheric disturbances.

Regional ranking of rain normalized annual vegetation production

Also for the rain normalized increment *NDVI a regional ranking was done. The image below (parklands_reg-rank-rnndvi-x _1982-2006) shows the average RNNDVI ranking position for all cells in the Parklands region with an average rainfall above 900 mm.
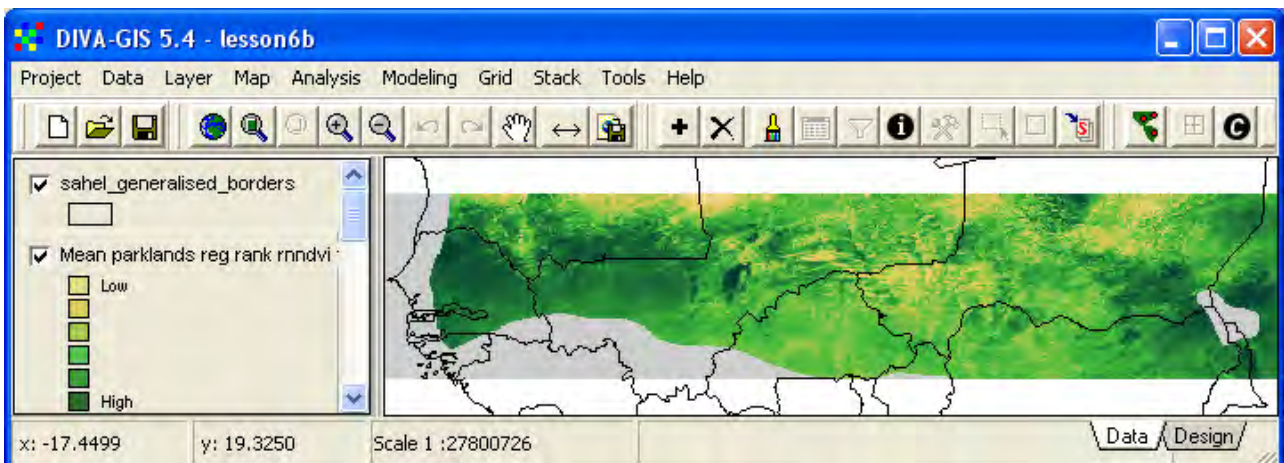
The variation in ranking position of RNNDVI for the period 1982 to 2006 (parklands_reg-rank-rnndvi-std_1982-2006) below shows a different pattern compared to the variation for the original *NDVI data above.
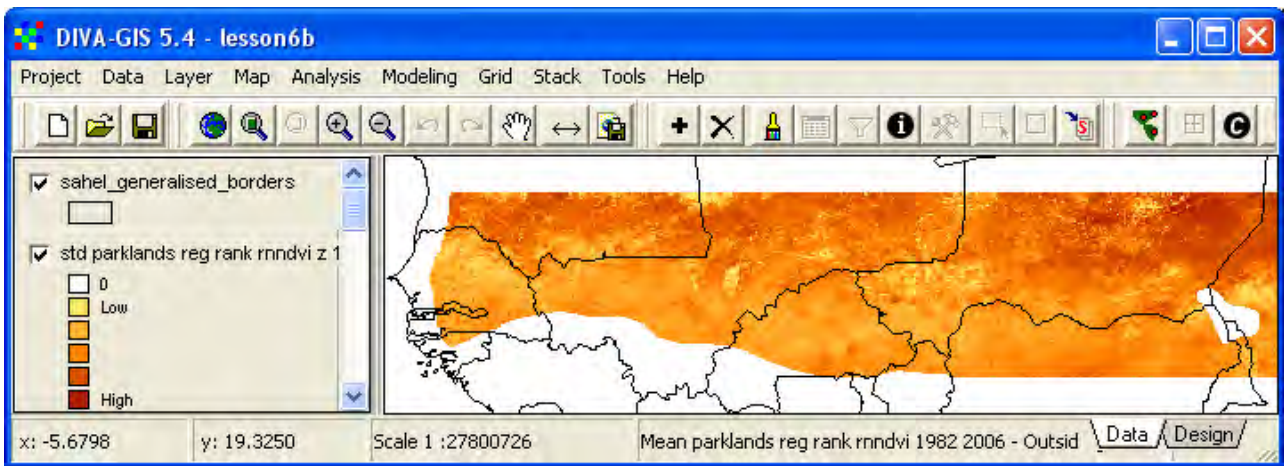
The relative trend in regional ranking of RNNDVI below (parklands_reg-rank-rnndvi-z-slope_1982-2006) shows that the vegetation production over rainfall has increased in the southern parts of the study area (except in Nigeria), and decreased further North.
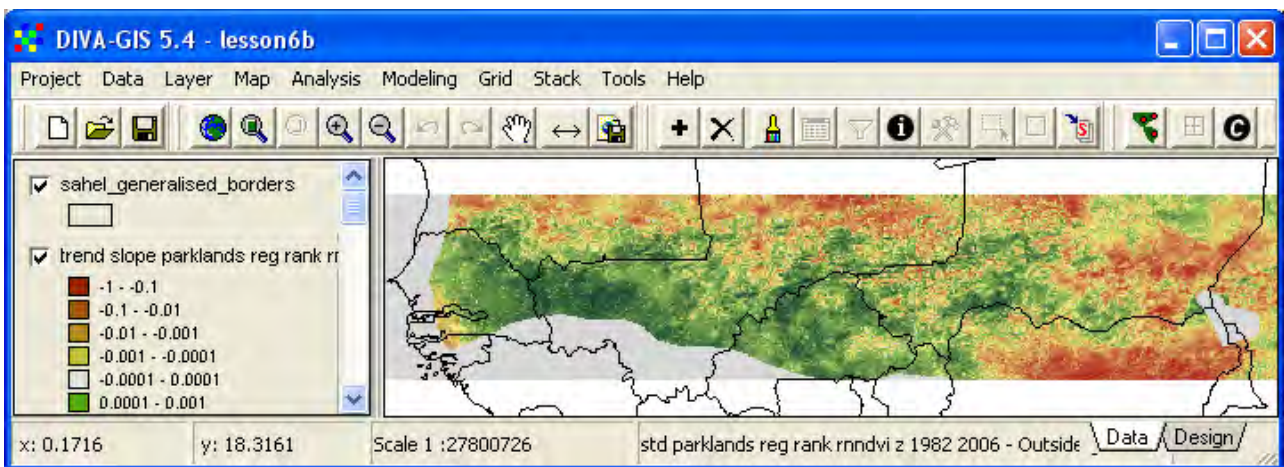

Focal ranking of annual vegetation production

A neighborhood (focal) ranking is also included in the project dataset. The focal ranking compares a cell with its 8 closest neighbors, and evaluates the relative vegetation production on a focal scale. This forces a fragmented pattern that is difficult to interpret. The image below shows the average relative focal vegetation production over the period 1982-2006 (parklands_foc-diff-ndvig-adj-x_1982-2006.grd).
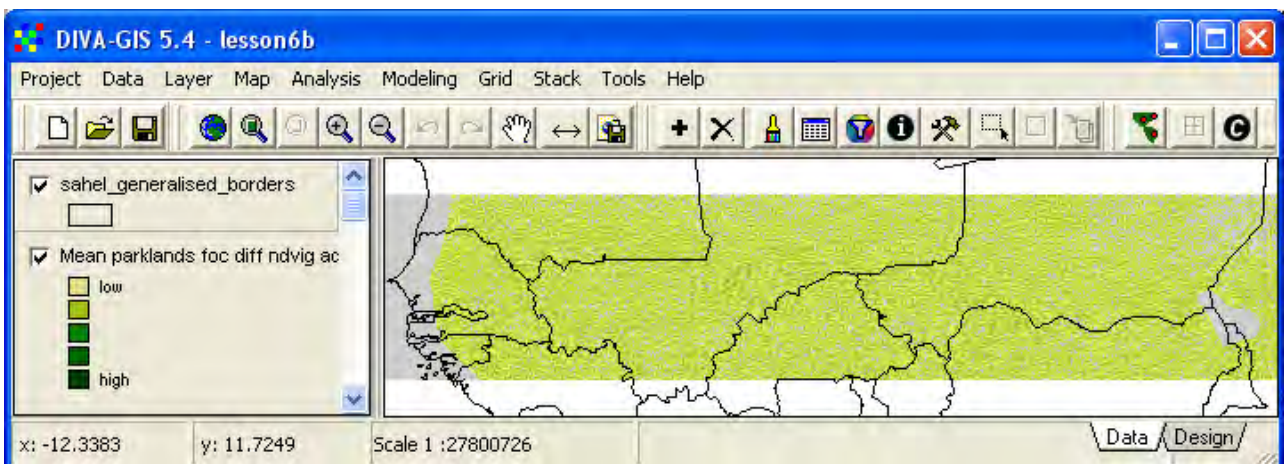

For the focal difference it is the variation that is of most importance (parklands_foc-diff-ndvig-adj-std_1982-2006.grd), as it can be used to separate areas with homogeneous vegetation production

from those with larger variations. This is of interest when identifying suitable field sites or selecting sites for further investigation. The image below shows that towards the drier north the focal variation in vegetation production decreases.
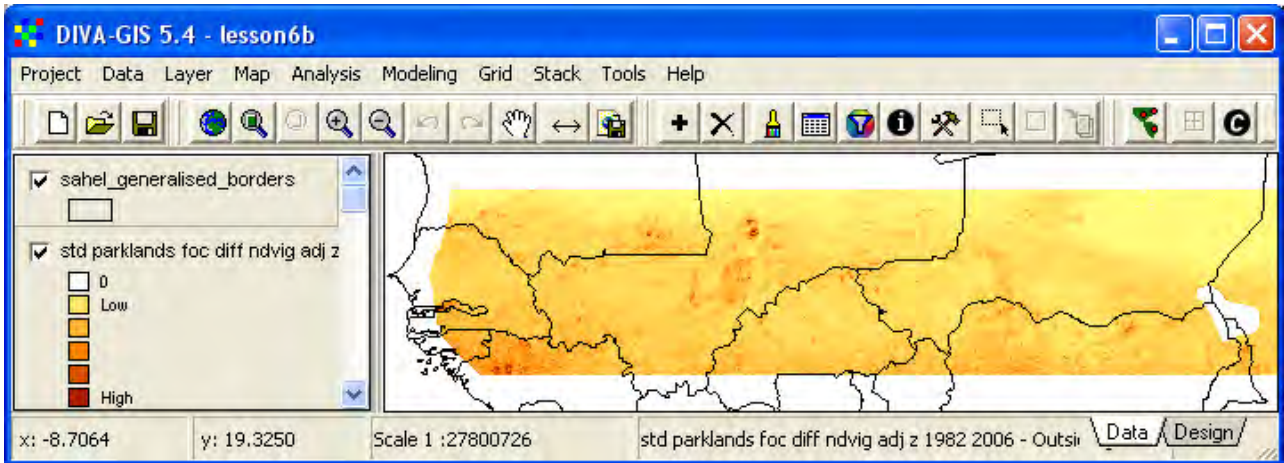

Identifying hotspots from ranking images

The regional and focal ranking trends and variations can be used to identify potential land degradation hotspot areas in an easy way. The most suitable image to use is the ranking trend from rain normalized NDVI (parklands_reg-rank-rnndvi-z-slope_1982-2006). Make this layer the active layer, and analyze the histogram for it (via the menu: Analyze – Histogram).
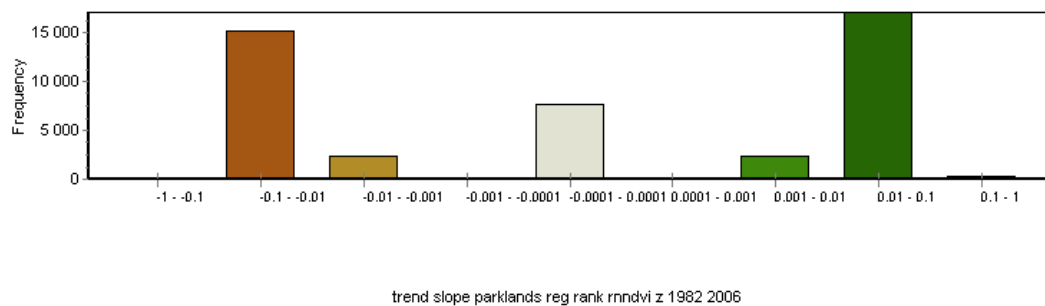
Change the Options for charting the histogram under the Options tab, until you identify a suitable number of cells you want to identify as most likely to be affected by land degradation, as shown in the example below.
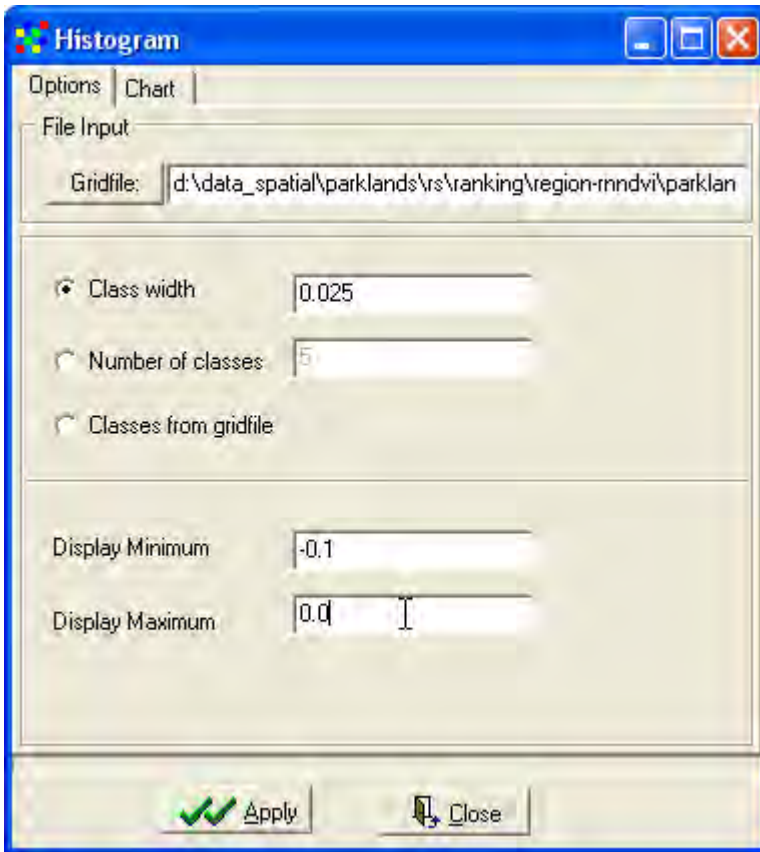
From the Options set above approximately 1000 cells end up in the range –0.1 - -0.075,as shown below.
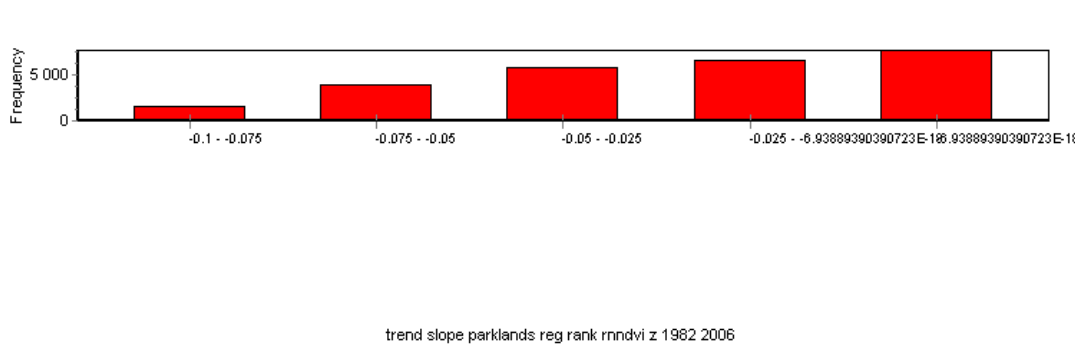
You can now use the information you retrieved from the histogram analysis in a reclass operation to single out those cells with the most negative trend in regional ranking of RNNDVI (via the menu: Grid – Reclass).
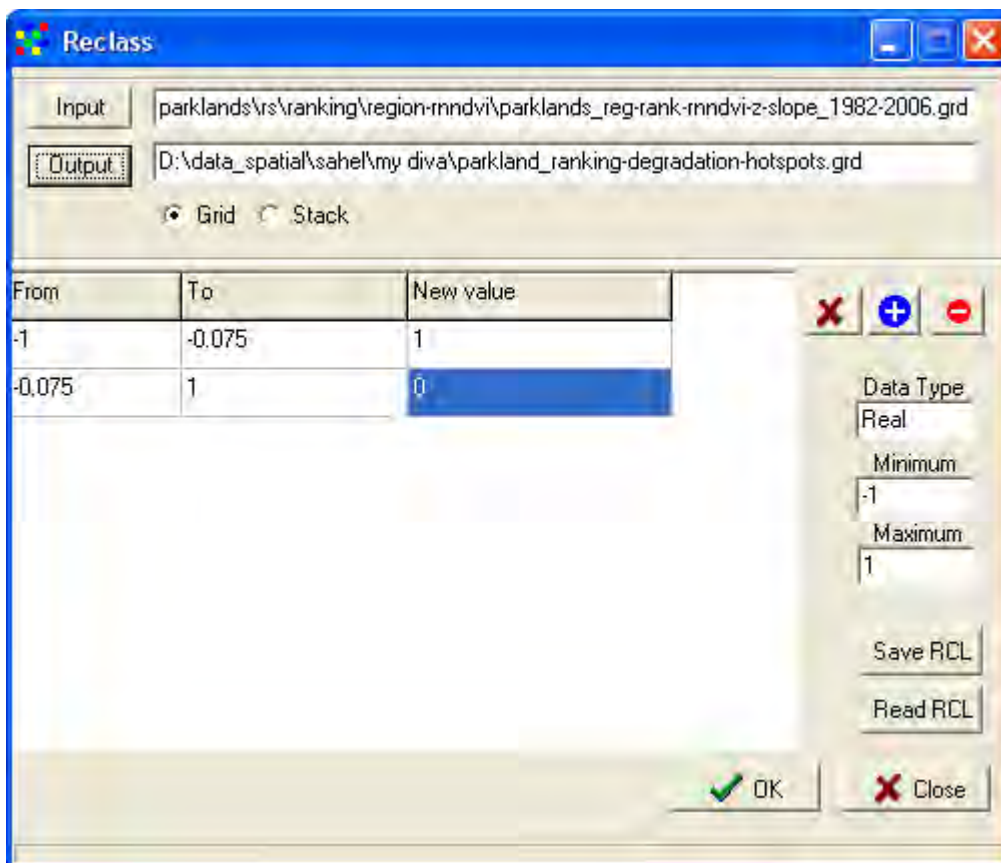
Symbolize the generated hotspot grid, and rearrange the display order to get the hotspot map, as shown below.
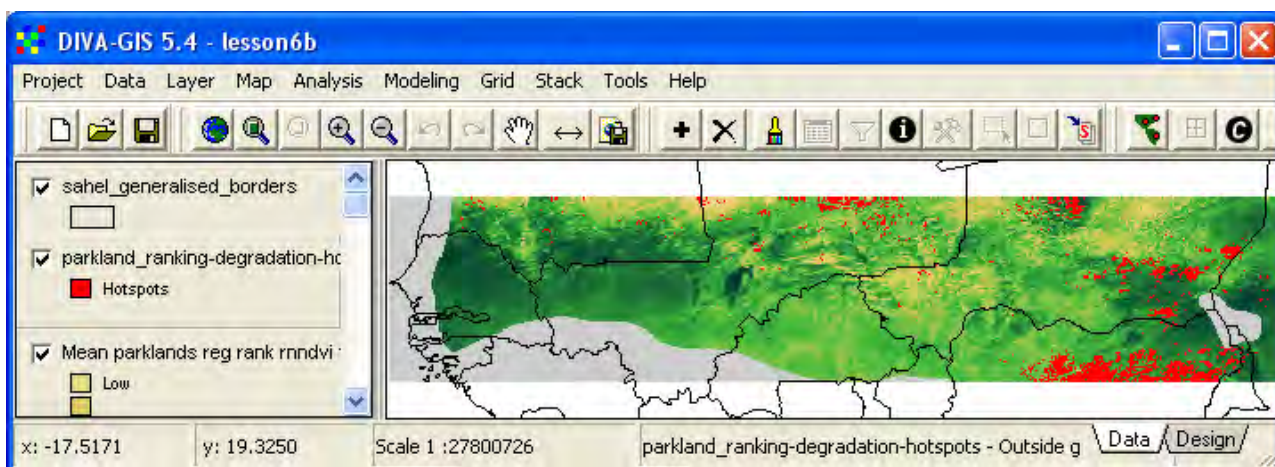

Almost all hotspots in the image above are in peripheral areas of the map. If you want to find the most likely hotspots in a sub-region (country, district or river basin) you can either create a mask or cut the ranking trend, and then redo the histogram analysis and reclassification for the cut grid. You can also use the focal ranking and the variation of RNNDVI for identifying hotspots in a similar way.

Multi Criteria Evaluation (MCE) for identifying hotspots and coolspots

Another alternative for identifying hotspots (and coolspots with improved vegetation growth) is to combine several indicators or vegetation changes. The method of combining two or more criteria (maps) for identifying a single objective (land degradation in this case) is called Multi Criteria Analysis, and is a standard decision tool also in other fields than GIS. Criteria can be of two kinds – constraints and factors. A constraint is similar to a mask in that it allows the identification of the

objective or not. A factor is assigned a weight that is used as a criterion in the decision model for identifying the objective.

Here you shall use one constraint, and three factors for identifying hotspots. The constraint you shall use are the countries included in the study. The factors are the three trend images of RNNDVI (derived from annual average *NDVI, annual maximum *NDVI and annual increment *NDVI). As we believe the increment index to be superior you shall assign a weight that is double as large (0.5) to the increment index compared to the other indexes (0.25). The weights should always add up to 1.

When doing the analysis you can choose if you want to do it for the whole of the included countries, or only for those parts covered by the Parklands. In the Do it on your own section you should choose a smaller region to do the MCE.

<u>Create a constraint map</u>

To create a constraint (0/1) map identifying the countries you must first convert the country polygons to a grid map, then reclassify this grid map to have the value 1 for included countries and 0 (or No Data) for other areas.

If you want to work with all the countries open the first DIVA-GIS project you created in this project (lesson6), if you only want to work with the Parklands, use the second project (lesson6b). The tutorial will use all the countries.

There are several options for selecting the countries included in the project. Either make the layer with countries as polygons the active layer, and open the Select window (e.g. by clicking the Query tool, ⚒, or via the menu: Layer – Select Records), and select the countries. Or use the interactive Select Feature tool, ⬚.

When you have selected the countries, use the Convert to Shapefile tool or go via the menu: Data – Selection to New Shapefile, and save the included countries as a separate shapefile.

Then convert the new vector layer to a grid by using the menu: Data – Polygon to Grid. Use the attribute MJ_NR as Field for setting grid values (no other Field will work), and one of the exisitng grid files of RNNDVI as template file.
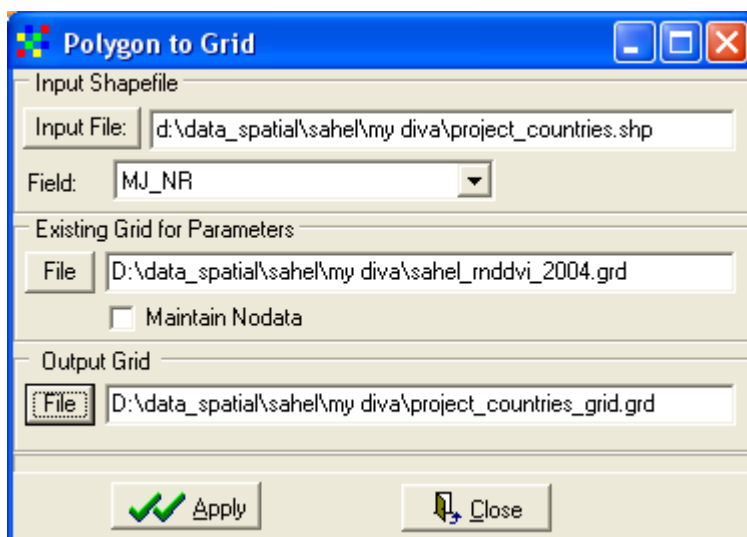
DIVA-GIS automatically sets areas outside the polygons in the vector layer to No Data in the grid output file. You must now use reclass (from the menu: Grid – Reclass) to set the grid value of all included countries to 1.
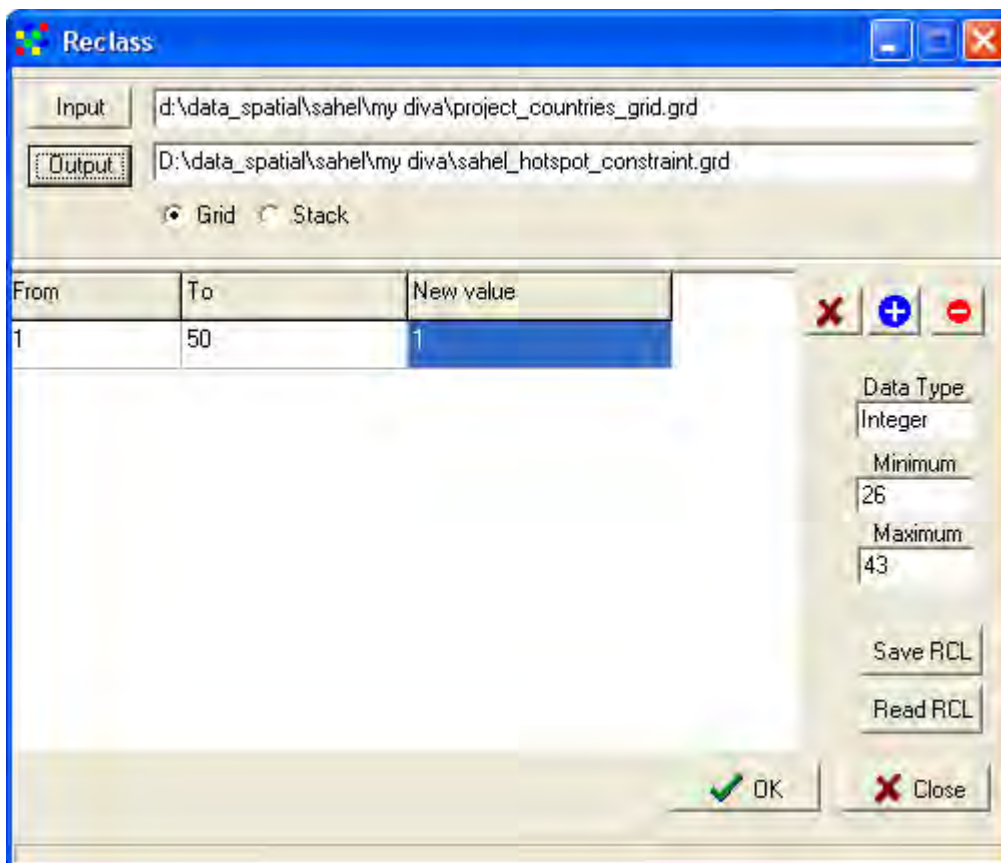
If you want to add more constraints to you MCE you can do that, and then use overly to multiply the constraints (0/1) layers to create an overall constraint. For now you will only use the country layer as a constraint.

Creating factor maps

You need to create 3 factor maps, one for each of the trends of the RNNDVI images (derived from average, maximum and increment *NDVI).

One of the most difficult problems in decision-making is to assign scales and weights to factors. You can choose to normalize the factors – that is set all factors to have a similar scale (e.g. 0 – 1), or use the original range of the input layers. This is especially sensitive if the layers represent very different features (e.g. vegetation cover and slope) that can not generally be directly compared. In this case we have the advantage that all input grids (the trends slopes of the normalized z-scores) have exactly the same range (namely from –1 to 1) and we do not need to consider normalization of the input data as it is already normalized.

The weighting of the factors is a major part of MCE. It is normally done using expert panels, where experts from different disciplines discuss and decide on the relative importance of factors. In this case you simply assign the weights you want, or use the weights suggested above.

Grid calculation

As you have the constraint map and the three factor maps, you are ready to execute the Multi Criteria Evaluation. The MCE is done as a map calculation:

MCE = constraint*(factor1*weigth1+factor2*weight2+factor3*weight3)

Where the weights should add up to 1.

You can easily implement the above formula in DIVA-GIS by using the Grid calculator from the menu: Grid – Calculator.
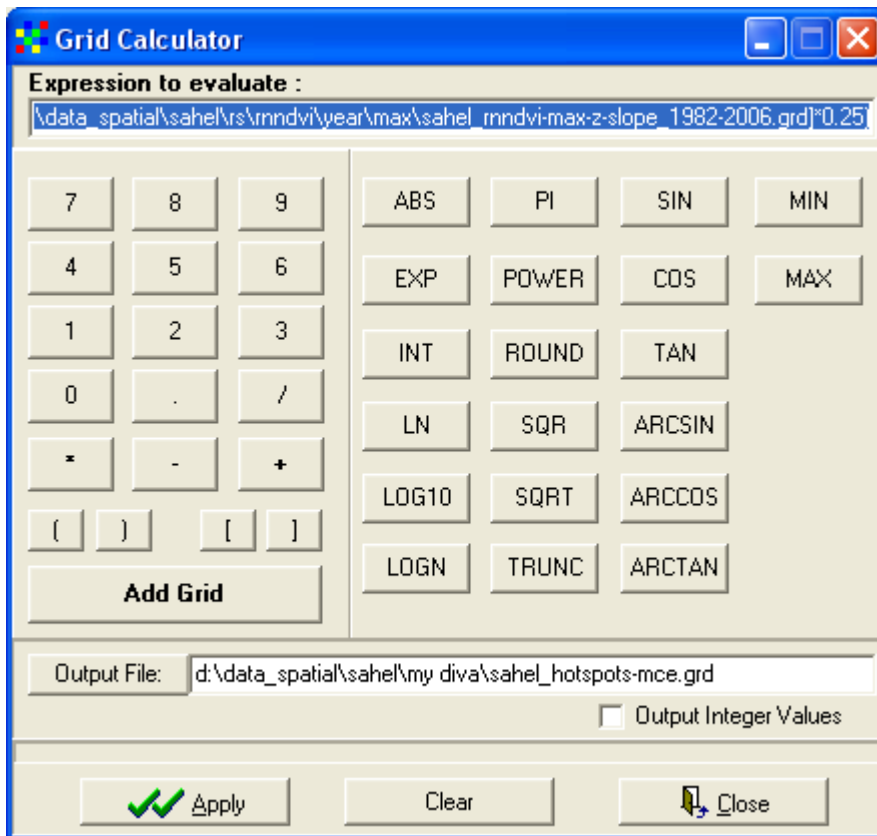
Use the Add Grid button, , to add the grid layers and the other buttons to put the operators and parenthesis needed. Below is the complete formula you need to add.

[D:\data_spatial\sahel\my diva\sahel_hotspot_constraint.grd]*

(

[D:\data_spatial\sahel\rs\rnndvi\year\average\sahel_rnndvi-average-z-slope_1982-2006.grd]*0.25+

[D:\data_spatial\sahel\rs\rnndvi\year\increment\sahel_rnndvi-increment-z-slope_1982-2006.grd]*0.5+

[D:\data_spatial\sahel\rs\rnndvi\year\max\sahel_rnndvi-max-z-slope_1982-2006.grd]*0.25

)

Give the MCE for identifying hotspots a logical name, and press Apply to run the MCE calculation.

As you used normalized data, and weights adding to 1, the MCE should have the same range as the input grids (-1 to 1 in this case).

You can analyze the MCE for identifying hotspots by looking at the histogram (see above) and then use the Legend to threshold the MCE to show only the most affected cells, as in the example below.
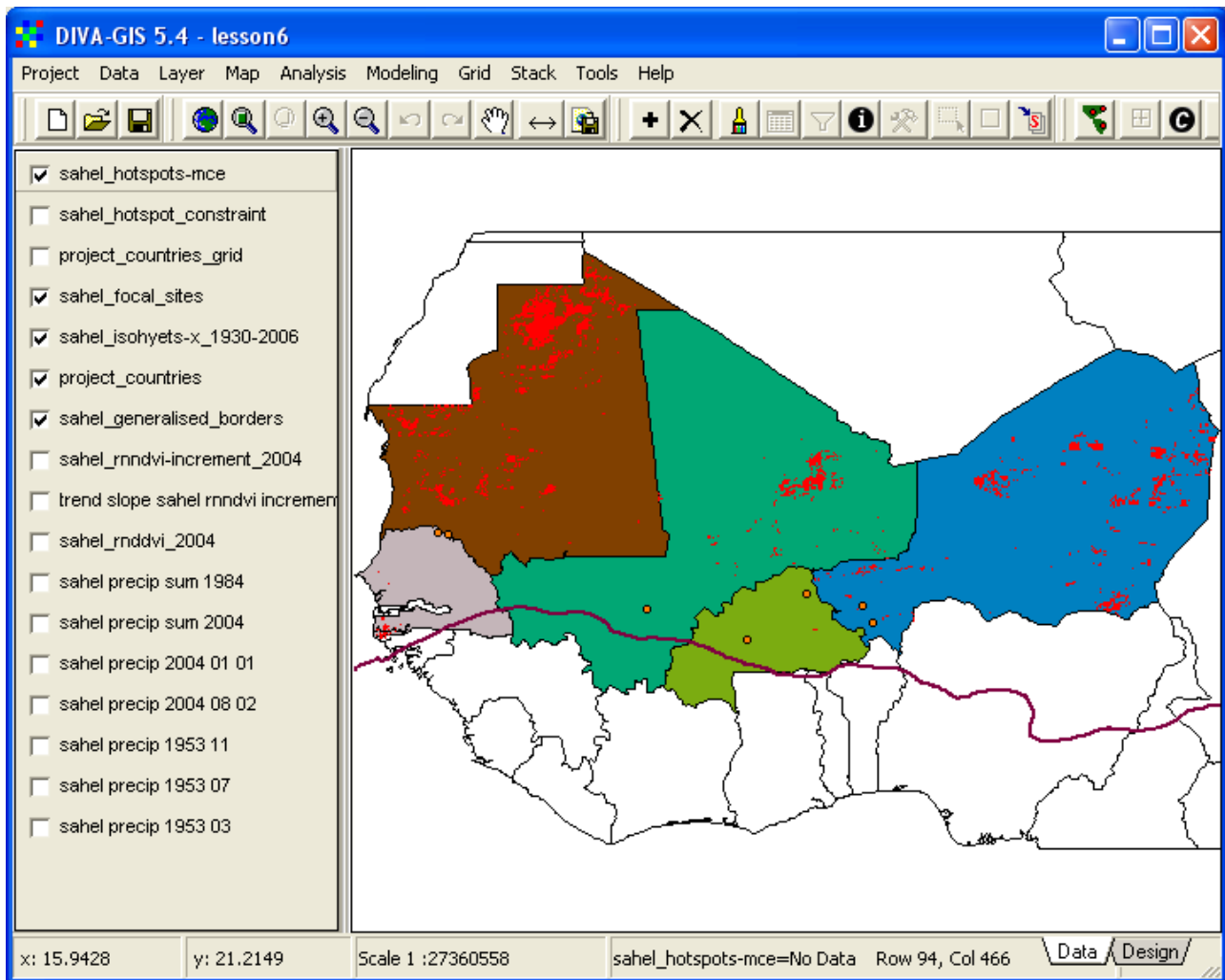
Try it your own 1 - Correlation between temporal trends in rainfall and vegetation production

In lesson 5 you did a statistical regression using an independent variable (rainfall) to explain the variation in a dependent variable (vegetation production) in a spatial context. That analysis clearly showed vegetation production to be strongly dependent on rainfall up to around 800 to 1000 mm of annual rainfall.

With the trend images of rainfall and vegetation production you can do a similar regression to test the influence of the rainfall trend on the vegetation production trend. It is better to use trends derived from the original data and not the normalized trend. Using a trend derived from the original data will be interpretable in terms of how much changes in rainfall affects vegetation production. If you use normalized data the regression formula can not be interpreted explicitly and is only valid for the period you analyzed (i.e. it can not be used for extrapolation) The principal steps you need to take include:

1. Make a stack with annual rainfall grids for the period you want to analyze

2. Make a stack for annual vegetation production for the same period (you can use any, or compare all, of the vegetation production indexes included in the dataset),

3. Calculate the trends in rainfall and vegetation production,

4. Cut the trends to fit a country, river basin or district,

5. Convert the selected country, river basin or district to a grid, using the cut trend grids as template,

6. Create a Boolean (0/1) mask of your selected country, river basin or district,

7. Apply the mask to your trend grids to remove pixels outside you study area by multiplication,

8. Make a regression using the cut and masked rainfall trend as independent and the cut and masked vegetation production trend as dependent variable,

9. Analyze the results from the regression, by using the transect tool and a histogram,

10. Symbolize two maps showing the cut and masked trends in rainfall and vegetation growth,

11. Compile the results into a short report on changes in rainfall and vegetation production in your selected area, including the two designed maps, histograms of the derived trends, one or two transects for both rainfall and vegetation production trends (using the same position for the transects in both maps), and both graphical and numerical results of the regression.

Try it your own 2 – Identify hotspots in a sub-region

You should finally also identify potential land degradation sites in the region you used above (Try it on your own 1). Follow the steps taken above in this lesson to create a hotspot map from either the ranking maps, or from the normalized trends in rain normalized *NDVI. To make the analysis even better, you can include the layers containing information on the significance of the trends (use them as constraints in the MCE). If you restrict your analysis to the Parklands area you can also use the ranking data as input in the MCE. The principal steps you need to take include:

1. Cut the grid layers you want to use as criteria to fit the grid data you used above (Try it on your own 1).

2. Normalize the input data to a common scale (either use the grid calculator, or the scalar function under the grid menu)

3. Assign weights to the factors you want to use in the MCE

4. Execute the MCE

5. Analyze the histogram of the MCE

6. Symbolize and design a map showing the identified hotspots

7. Compile the results into a short report on hotspot identification using MCE, including the designed maps and the histogram of the MCE result.