6 Results of Moveg Draa

This chapter presents the results of all approaches and routines stated in the previous chapters. Guided by the module structure, it concluded all results in two parts. The first part concluded all results based on the measurements of station based results. This part also included an overview of the results of these methods. The second part gave an overview of multi-station results, like gradient and other spatial outcomes.

6.1 Results Climate Data

This sub-chapter summarizes all calculated measured and calculated meteorological data along the transect given in Figure 58.

![Measurement gradient](image)

**Figure 58 Measurement gradient**

Using the transect given in Figure 58 this chapter presents an overview about the situation inside the catchment, picking example data to demonstrate certain facts.
6.1.1 Wind

Wind is the driving factor for all particle incidents in the atmosphere (Oke, 2003). The wind speed inside the catchment is investigated on two selected stations, TZT and TAO. Both are inside the High Atlas mountain range. The exact orientation of the mountainous plateau of TAO is SW to NE and TZT is located on a platform that is framed S to W by mountains. Both stations have a wind direction that follows the orography of the location.

The velocity of stations TZT and TAO (Figure 59) shown that wind direction has no significant influence on the mean win velocity. This is important because it is now possible to negate wind direction in calculating transpiration rates and evaporation, but keeping in mind that the wind direction is rather important for Luv/Lee effects, as well as the dew point.

6.1.2 Temperature

The temperature inside the investigation area follows the classical seasonal climate (Figure 60) that can be expected in arid areas (Le Houérou, 1996; Born et al., 2009).
Figure 60 includes all data measured starting in 2000/2001, till the end of 2008. The temperature ranges from cold winters to hot summers. The yearly temperature gradient varies from 15° up to 30° in the southern areas. According to (Potter & Klooster, 1999)
savannas and wooded grassland stretch at least 16 to 11315 GDDs. By taking Toujgalt as example a total of 4032 GDDs on the base of 280 days over 5°C (see Chapter 5.6 for details) and a mean air temperature of 14.4°C was calculated.

6.1.3 Precipitation

Following the vegetation classification of (Potter & Klooster, 1999), semiarid shrub land inherit a rainfall ranging from 276 to 0 cm per year. Looking at the examples in Figure 61 and from 52 to 300mm.

Figure 62 the mean annual precipitation varies from 52 to 300mm.

Figure 61 Climate Station EMY
The high atlas mountain range is then to be classified as savanna and wooded grassland (comp. (Finckh & Oldeland, 2006)). By looking at the spatial distribution in Figure 63, it becomes clear that the mean distribution of rainfall events (daily based) inside the area, indicates no significant yearly varying distribution of rainfall south of the Anti Atlas (Bou Skour).
For the stations south of Bous Skour the most notable rainfall occurs during September to November. For stations north of Bou Skour precipitation takes place mainly in March/April and October though it has a high variance (comp. chapter 5.6).

Figure 64 shows the precipitation in the southern areas (represented through EMY here, more stations and figures can be found in the appendix) are on a very low level with a high variation coefficient throughout the year. This means that the small amount of rainfall strongly varies and is only predictable through the general weather situation rather than by climatology.

For the northern stations (Anti Atlas and northward) the variation coefficient remains at a high level for all stations with high variation (as seen in Figure 65) in winter and spring. But one can see in Figure 65 that the fall/winter rainfall is much more reliable than that in the southern part of the investigation area.
All stations north of the Anti Atlas show a significant fall/winter/spring rain regime. This is confirmed by looking at historical long term development. This confirms the fall/winter/spring rain regime (see Figure 66.)
High values in coefficient of variation in summer are due to the difference between wet and dry years. On the long term track the regime is very constant in October/November but variable with regards to rainfall amount (Figure 67).
Figure 67 mean rainfall during various Decades for the station Agouim

These tendencies are further strengthen when taking a look at the relative anomalies of a drought year (Born et al., 2008).
Figure 68 Relative Anomalies for station OZZ (Source: Kai Born)

The larger dry (marked red) and wet periods (marked blue) indicate large inter-annual variations, which have a great impact on food production systems (i.e for the sub-Saharan system: Nicholson et al, 2006; Benson and Clay, 1998).

In conclusion it can be stated that the precipitation variation is stable over the last 30 years. The precipitation fluctuations over the last 50 years are an alteration of dry and wet years, but always with reliable precipitation.
6.1.4 Transpiration and Evapotranspiration

Using the formulas described in Chapter 5.6, transpiration rates, like PET and ET, was calculated. These rates are an important factor for the percentage loss of water for plants (comp. (Kolb & Sperry, 1999) and used in the ANPP module.

Looking at the N-S profile, an increase in the total sum of PET from North to south can be seen (Figure 71). The TZT station has great standard deviations because of failures (due to vandalism).

![Graphs showing mean annual sums ET, PET, evaporation and transpiration rates with their standard deviation for selected stations. Note: Tizi-n-Tounza Station inherits noncredible data.](image)

One interesting fact is the increase of transpiration rate when going southward. The only exception is Trab Labied, which has a very low vegetation cover. Notice that the really substantial standard deviations occur due to cloudiness, wind and exposition. For example in JHB, you see a very small standard deviation. One reason my be that JHB station is a south oriented, small vegetation cover and high net radiation area. This caused a very small varianion throughout the year, which is reflected in the measured data.
When looking at the TAO station one can be notice that the greatest ET occurs during May. This shifts to June for the southern area of EMY (Figure 70).

Figure 70 Evapotranspiration stations TAO and EMY

Figure 71 mean daily sum Potential Evapotranspiration [mm]
The calculated pattern of ET (Figure 71) reflects the N-S profile and the seasonal peak (June-August). Although the calculated values for the Atlas mountain range are less seasonal than rates calculated for the basin of Ouarzazate (TRL) and southward, there is, as expected, an notable increasing inside the catchment.
This trend is turned for the evaporation rate (Figure 72) with a more seasonal signal for the atlas mountain range. Although the N-S profile is more dominant then in PET, the clear breaking is shifted from TRL to TAO station. The calculated ET reflects the presented vertical altitude profile of the vegetation signal (comp. MODIS NDVI4.2.1).
6.1.5 Radiation

The mean short wave net radiation, a standard measured parameter, is an important parameter to estimate the radiation balance.

![Mean Net Radiation TAO 2001-2008](image)

Figure 73 monthly mean Net Radiation TAO station

The measured seasonal trend of the measured radiation (Figure 73) peaks during June and is lowest in Dec/Jan. The yearly cycle of the inclination angle, which reaches its peak during June/July is, as expected, repeatable by the measured values. The net radiation, or radiation in general, is the driving factor for plant productivity. Due to failures during operational time this factor is not used for productivity calculation. Instead an atmospheric radiation model is used to simulate the energy input on the system (see chapter 6.6.).

6.2 RCN Results

The RCN module is designed to calculating the actual soil moisture depending on precipitation and preliminary moisture. Although it was designed to calculate runoff, the Run-Off Curve number is the most important module to calculate the plant available water.
The module calculates soil moisture from 2001 (start of the climate measuring) until the end of 2008 as a 16 day sum. This sum is the available water to plants. The predicted values (Figure 74) are fluctuation and representing the great amount of storable water.
Soil water as function precipitation indicates the amount of water inherited by an soil profile, defined by the amount of water capacity (AWC). The damping effect is to the evaporation, based on the calculation (Weber, 2004).

Since there is no other soil moisture available, since (Weber, 2004), a comparable validation method has to establish. RCN originally calculates run-off, it is possible to validate the model with other hydrological models. The SWAT calibration for the upper catchment of the valley Drâa (Busche, 2009), integrated in the IMPETUS ISDSS HYDRAA, are served as validation data.
The runoff, calculated by both models, differs significantly. MD always underestimates the runoff by SWAT (Figure 76). This overall underperformance reflects in the different driving factor of precipitation (comp. Figure 77).

Figure 76 Compare ISDSS and MOVEG Drâa for TAO Station

Figure 77 Compare Precipitation of MOVEG Drâa and SWAT (note that MD only calculates until end of 2008)
SWAT calculates an altitude based virtual climate station, which is slightly different to the measured data. The principal higher rainfall (Figure 77) indicates SWAT approach to recalculate the measured precipitation to an slightly higher altitude sub catchment.

![Taoujgalt (1870 m)](image)

**Figure 78** Difference MD to SWAT for station TAO

The compared result for the station TAO (Figure 78) and IMS (Figure 79), as proxy, indicates a significant coherency between both models.
The RCN module results described in this chapter is intended to calculate the amount of available water in the soil profile. The temporal agreement for all stations ranges from an IA of 0.71 to 0.5, providing exact information about the amount of water for all investigated stations. Our RCN algorithm are calibrated for the stations inside the investigation area by the measured values and cross-validated with SWAT model results. The results seems to be highly robust, as it not depend on a particular soil typ or set of field measurements, as used on the stations.

Figure 79 IMS Precipitation Runoff difference between ISDSS-MOVEG
6.3 Temporal and spatial calculation on the Vegetation cycle and Land Cover dynamic

6.3.1 Lag Results

Precipitation in the rapid growth stage is important for vegetation activity in both stages (under the assumption that precipitation impacts the vegetation activity in the rapid growth stage, and there is not a large time lag and precipitation 1–2 months before the mature stage impacts the vegetation activity in the mature stage (Schultz and Halpert 1993; Miyazaki et al. 2004)).

![Figure 80 TAO Station monthly distribution of plant relevant parameters](image)

Lag as described in Chapter 5.9 is here displayed as a number of scenes (16 days) during which the delayed reaction occurred. The Lag factor is calculated as a yearly factor for every vegetation period, which are defined from September to August.
Lag is seen as a temporal and spatial calculation of the vegetation cycle, under the presumption that rain is one of the driving factors for land cover dynamic, for a given rainfall input. Using the maximum co-variance method it can be shown that most of the moisture given by rainfall is correlated to a vegetation growth offset of 16 to 32 days. This means that rainfall is converted to vegetation activity with a delay of roughly half to one month. This must be seen in the context of plant nutrification documented in chapter 5.9. Figure 81 shows that the lag is increasing for the phenological years 2002/2003 and 2004/2005. This might be explained through a dry year 2001/2002 and more wet years afterwards.

Therefore the phenological reaction and the phenological cycle can be described as an reaction of temperature and precipitation.
6.3.2 Phenological Cycle

The phenological cycle can be displayed as a deviated product of climatologic data or as product of the earth observation systems. This chapter introduce the climatologic phenology.

The length of the vegetation cycle is a good indicator for describing the possibility of vegetation growth and therefore the activity period of a vegetation formation or location. This can be expressed as pluviothermic ratio (Emberger, 1939). Figure 82 shows the vegetation length inside the high mountain Atlas range. The Figure reveals two important things: Firstly, the decrease of total days of the vegetation length with increasing altitude. Secondly, temperature stress having relevance, since temperatures below 5°C are a significant limiting factor.

![Figure 82 Length of the Vegetation period](image1)

Figure 82 shows us that the same data without water stress enables a significantly greater number of vegetation growth days. And it gives a short view on the TRB station. Water stress seems to be no significant problem there (Figure 83).

![Figure 83 Difference % of Vegetation growth days without Water stress to normal Vegetation growth days (>5°C)](image2)
It can be concluded that number of growth day’s without water stress is even higher inside the Atlas mountain range and very low inside the basin of Ourazazate. That means that the climatology derived water stress significantly dropped within stepping into the mountains.

Figure 84 shows an increasing Emberger index corresponding to altitude.

![mean weighted Emberger Index](image)

**Figure 84 weighted mean Emberger Index**

With increasing altitude an raising Emberger Index can be stated (Figure 84). This is confirmed by the Aridity index.
The Aridity index at Figure 82 and Figure 85, calculated after Middleton and Thomas (1997) stated that the vegetation length actually decreases with altitude and aridity also rises with altitude. This can be explained not only by rising water stress (Figure 84) but also by higher water variability with higher relief energy and therefore faster drying of top soil because of lower soil profiles (see also Klose, 2009).

This is of relevance for land use, because a higher stress factor (comp (Baumann, 2009) for vegetation suggest a differentiated land use.
6.3.3 Vegetation Cover Calculation

The vegetation cover calculation is based on the monitored ground truth points (comp. Chapter 4.2.1). As stated in Chapter 5 the regression approach should reflect the relationship between different NDVI and their corresponding total ground cover. This is done automatically inside the module. Table 6 shows an example of the Geodata base excerpt for the station EMY.

Table 6 EMY Ground Cover data

<table>
<thead>
<tr>
<th>Date</th>
<th>Vegetation Cover [%]</th>
<th>NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td>P2 08.03.2007</td>
<td>7.5</td>
<td>0.1027</td>
</tr>
<tr>
<td>P2 06.09.2007</td>
<td>5</td>
<td>0.0977</td>
</tr>
<tr>
<td>P2 05.06.2008</td>
<td>5</td>
<td>0.0890</td>
</tr>
<tr>
<td>P2 01.10.2008</td>
<td>2</td>
<td>0.0865</td>
</tr>
</tbody>
</table>

Table 6 shows the acquired data for the ground truth point P2, which is very near to the climate station EMY.
It is now possible to use those four points per GCP to calculate a logarithmic regression formula. Why use a logarithmic approach? As seen in Figure 87 the logarithmic function approximates the asymptote to the maximum.
This is crucial, because buffering the vegetation cover against high NDVI is difficult (comp. Bannari et al., 2002;du Plessis, 1999;Geerken & Ilaiwi, 2004). It is neither plausible nor logical that the vegetation cover extends maximally. In this case the maximum vegetation cover is 62.819% if the NDVI is 1. The quality criterion for all stations is listed below. The complete list of all points is available at the appendix.

**Table 7 Quality Criteria Cover function**

<table>
<thead>
<tr>
<th>Station</th>
<th>GCP</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMY</td>
<td>P2</td>
<td>0.73</td>
</tr>
<tr>
<td>ARG</td>
<td>P1</td>
<td>NaN</td>
</tr>
<tr>
<td>TAO</td>
<td>P26</td>
<td>0.74</td>
</tr>
<tr>
<td>BSK</td>
<td>P10</td>
<td>0.39</td>
</tr>
<tr>
<td>MGN_f</td>
<td>P43</td>
<td>0.2</td>
</tr>
<tr>
<td>TZT</td>
<td>P32</td>
<td>0.97</td>
</tr>
<tr>
<td>TIC</td>
<td>P37</td>
<td>0.98</td>
</tr>
<tr>
<td>IMS</td>
<td>P39</td>
<td>0.99</td>
</tr>
<tr>
<td>TRL</td>
<td>P19</td>
<td>0.86</td>
</tr>
<tr>
<td>IRK</td>
<td>P4</td>
<td>NaN</td>
</tr>
<tr>
<td>JHB</td>
<td>P3</td>
<td>0.44</td>
</tr>
</tbody>
</table>

The calculation itself is a non linear iteration approach getting the data from the database and a corresponding image by using the formula \( Y = \theta \ln(x) + \theta \). The results are acceptable for most stations. Unsatisfactory stations, like MGN_f and JHB are explained by their terrain and vegetation configuration. The JHB Station for example is a very thinly vegetated station in a rocky environment. The MGN and BSK Areas seem problematic because of steep hills and assumed high land use pressure.
6.3.4 Leaf Area Calculation

The Leaf Area (LAI) calculation was not available through the standard NASA Land product series since NASA declared most of the natural vegetation area as bare surface/desert and therefore with a vegetation cover of 0, which is wrong.

The LAI is described as leaf area (m²) per ground area (m²). In today's remote sensing literature numerous approaches exist (Burrows et al., 2002; Carlson Toby N. & Ripley David A., 1997; Carlson & Ripley, 1997; Chen Jing M. & Cihlar Josef, 1996; Foetzki, 2002; Law Beverly E., 1995; Myneni et al., 2006; Patenaude et al., 2008; Qi J. et al., 2000; Tian et al., 2004; Turner et al., 1999; White Michael A. et al., 2000; Wissskirchen, 2003). There are other, non remote sensing, scientific approaches like (Diekkrüger, 1996), which are determined by Equation 18 LAI Diekkrüger (1996)

\[ \text{LAI} = \frac{\ln(1 - \text{cover degree})}{-0.4} \]

This Diekkrüger approach is based on the ground cover and seems predestined. Nevertheless an approach after (Myneni et al., 1995b) was also tested. It determined a specific leaf area index (leaf area (m²)/leaf mass (kg) from field measurement.

![Figure](Image)

**Figure 88 SLAI and LAI comparison (Source: Baumann (2009) )**

By using the approach of (Myneni et al., 1995c) it was possible to develop a specific approach, which is separated into separate altitude steps of 400 - 1200m, 1200-2300m as well as above 2300m (Figure 89).
Since LAI is coupled with the standing biomass (Figure 90), a great variance in biomass between 1200 to 2300 m and in the quantiles of the biomass which might explain the higher median in Myneni approach for this area.

The overall performance by the Diekkrüger remains unsatisfactory, because of there high variation.
Especially the great standard deviation makes this approach less useful. This can understood in greater detail through a comparison of both approaches and the LAI measured by Baumann (2009).
The different methods for calculating LAI display that the measured LAI is significantly different from the calculated LAI's. This can be explained by two reasons. The measured LAI is calculated on the basis of about 60 of 300 species inside the area (oral, Baumann) and is only representative for all species that have leafs. That excludes mainly *Hamada spec* and *Juniperus spec*. *Hama scoparia* is the name giving dwarf shrub in inside the area between 1200 and 2300m a.s.l. The Juniper tree and Chushion bushes inside the high atlas mountain range add a significant amount of LAI to the measured (comp. (de Jong *et al.*, 2008; Finckh & Oldeland, 2006). Baumann's LAI is a measure of the feedable (i.e. green) biomass and the Specific Leaf Area Index. The feedable biomass is calculated by a factor that represents the fraction of feedable biomass to total biomass per plot. This means that the factor is a mean average of all plants per altitude and use. The biomass per plot is calculated by another factor from the total cover of all species to biomass per plot. This factor is calculated by a regression of the investigation area, namely the high Atlas mountain cover and biomass. The specific leaf area index for every species is calculated by taking 10 individuals and 10 of their leafs. Knowing the mean SLA/per species and knowing the coverage of every species Baumann calculated the weighted SLA/per plot. The result is a mean value of SLA per altitude and usage (pastures or exclosure).

This is also calculated from two different sources. Calculating LAI from a remote sensing perspective means in this case to extrapolate LAI from the FAPAR and therefore from the NDVI. The NDVI represents the vegetation activity (Myneni *et al.*, 2006). Therefore it represents the sum of chlorophyll that uses PAR radiation and is described by the fraction of the incoming solar radiation in the photosynthetically active radiation spectral region that is absorbed by a photosynthetic organism (Details are discussed in Chapter two and three, as well in chapter four).

By comparing degraded areas (25% percentile of all LAI in 3 different altitudes) of the Diekkrüger and Myneni approach (including Standard deviation) with the pastured median of the cage experiment, the difference is inside the standard deviations of the methods. This leads to the conclusion that the method of Diekkrüger is insufficient because of its relatively great standard deviation. The method of Myneni seems to be appropriate because it reflects a common method in remote sensing, has an acceptable standard deviation and represents the measured LAI under the circumstance that the measured LAI does not include all green active vegetation.
By using this approach it is possible to calculate the LAI for the whole catchment (Figure 93).

The spatial analyse can be summarized for all stations by Figure 94.

In Figure 94 it is visible that the high Atlas mountain stations inherit a much larger variation than the more southern stations.
6.3.5 Carbon Fixing estimation

Carbon fixing is the process of accumulating carbon in stable organic matter. The carbon fixing approach was developed from field experimentation. Therefore the measured difference in standing biomass is taken and calculated in regression with the amount of PAR during the experiment time.

Table 8 Calculated C-Fix Factor

<table>
<thead>
<tr>
<th>Experiment</th>
<th>NPP</th>
<th>DoM&lt;sup&gt;11&lt;/sup&gt;</th>
<th>NPP/day</th>
<th>NPP in g/m²</th>
<th>Radiation</th>
<th>C-Fixing Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>TRLG10</td>
<td>103.8</td>
<td>215</td>
<td>0.482983282</td>
<td>0.00482983</td>
<td>210.873095</td>
<td>0.005863418</td>
</tr>
<tr>
<td>TAOG10</td>
<td>48.2</td>
<td>217</td>
<td>0.221904847</td>
<td>0.00221905</td>
<td>233.298358</td>
<td>0.002434978</td>
</tr>
<tr>
<td>AMSG10</td>
<td>63.7</td>
<td>391</td>
<td>0.162857653</td>
<td>0.00162858</td>
<td>242.732462</td>
<td>0.001717593</td>
</tr>
<tr>
<td>TZTG10</td>
<td>195.2</td>
<td>388</td>
<td>0.50299855</td>
<td>0.00502999</td>
<td>147.947653</td>
<td>0.008703594</td>
</tr>
</tbody>
</table>

The result is the dependency of carbon fixing on incoming radiation. A first approach uses linear dependency as indicated in Figure 95.

A linear regression comes to its limit when encountering varying radiation amounts. To compensate this effect a decreasing, polynomial approximation was used. This function imitates the biophysical process of an optimal radiation process, based on the measured data. The results are shown in Figure 95.

<sup>11</sup> Days of Measurement
This approach has two restrictions:

It is limited to 125 and ~250 MJ/m² and the calculation of the maximum point is an approximation and is not regarded as universally valid or may not be effective outside the catchment.

First test indicated the calculated carbon fixing (or LUE) factor to be valid. This factor is strictly speaking only valid for the northern area of the catchment, but is used on all stations under the presumption that carbon fixing is stable over the whole region.
6.4 Pre Regression Results

First generalized linear model (GLM) tests reveals that the combination of rainfall, temperature and ground water seems to be a good approach to fit the data and is therefore used inside the regression formula. The ANPP is not used for forecast purposes because of its usage of meteorological data (like Evapotranspiration) and a possible collinearity. Furthermore the ANPP needs NDVI as an key input parameter.

Before starting the regression, the data needs to be checked for significance and other statistical data that could be preliminarily necessary for a regression. All tests that are presented here are encoded into the model and combined with statistical limits. This produces an error message if one test fails. In this way the user is able to analyze the error and fix the data or even drop the data set. An alpha level of 0.05 is used for all statistical tests. All input parameters are checked whether they are usable inside the regression.

As already stated the time period of 2000 to 2006 is used for calibration purposes, and 2007-2008 for validation purposes. The original NDVI signal (as exampled here for the TRL-station) can be described as Figure 96.
Figure 96 Raw - NDVI signal for the station TRL over the period 2000 until 2009 showing the inter-annual vegetation signal fluctuations

Since data harvesting for every station is taken from an bounding box near the stations, fluctuation is averaged but indirectly inherits the spatial fluctuation around the station. By taking the mean for every time step the temporal fluctuation can be shown in a box plot.
As Figure 97 shows the raw data entails some failures (below 0) and some stations, like Tichki, indicate a high amount of outliers and a high variance. This was used as base of the definition for the data filter, which is fixed to a double standard deviation. This eliminates outliers and improved the signal quality. With this applied filter, the data is checked for multicollinearity.

Figure 98 VIF and tolerance (method see chapter 5.10)
As seen in Figure 98 all data used is below a VIF of 5 and greater than 0.2. This enables the predictors realiable.

The normal distribution test in Figure 99 shows that the data is below the threshold. The treshold is calculated by number of case and level of significance. This means that the data is normally distributed and usable in a regression. On the base of this knowledge the significance of the NDVI signal is tested by the probability of valid data within a two standard deviation area.
Figure 100 NDVI significance with confidence level $p=0.05$

Figure 100 shows that most of the NDVI signal is significant. There are some problems inside the high mountain Atlas range due to shadow and dust effects (see ‘known problems’ on the NASA website).
6.5 Regression

This chapter introduces the results of the calibration and validation phase of the NDVI regression. It uses the approach introduced in chapter 5.15. This chapter concludes the theories from Chapter 5.1 and presents in which way the chosen input parameters influence the NDVI. This chapter is divided into two main subjects. Calibration and quality assessment, as explained in chapter 5.10, are done in a calibration and validation phase. By minimizing the differences between observation and model output the model is altered until an optimum (Daren Harmel & Smith, 2007). Goodness-of-fit indicators (defined in chapter 5.14) for the training phase 2000 until 2006 and the validation phase 2007-2008 indicates the calibration. This chapter presents should give an excess overview on how the calibration was done, and under which quality. As explained in chapter 5.10 the data is separated into increasing and decreasing data. Figure 101 shows an example distribution chart. The red line indicates the separator for increasing and decreasing data.

![Figure 101 NDVI data separation (demonstration data)](image)

By using the regression approach described in Chapter 5.14 a multiple linear regression formula is calculated for every station. The quality of the linear regression is at first evaluated by a t-test. The null hypothesis here is that the predicted output of multiple linear regressions is the same as the observed NDVI signal.
The t-values indicate that the Null hypothesis declines the 0.95% confidence interval for some stations. This means that the linear regression didn’t fit the original NDVI signal. The $R^2$ (as explained in Figure 103) will not be used any further, because of the unsteady NDVI signal and the very low variance (see Colditz, 2007 and chapter 4.3).
The next step to improve the results is using non linear regression. By using this technique I compared the predicted NDVI signal with the observed original using a linear regression.
Results of Moveg Draa

Figure 104 F- and p-Value after the linear regression step and after the non-linear regression step
In Figure 104 the F-Values can be significantly reduced during the nonlinear regression. The F-Test in regression models should test if the coefficient of determination is zero. This can be denied, because the F-Value is significantly greater than the critical F-Value (3,120)~2,70. The corresponding p values in Figure 104 show that it can be assumed that the result is significant, because the Null hypothesis that the p-value is smaller or equal to the significance level (in this case the usually 95%) can be rejected. This can be underlined by the reduced sums of square error (Figure 105).

The regression quality shows that the regression result can be significantly improved by using the described regression combination. The estimation of the regression coefficients (or predictors) is stable which is shown by the total (corrected) sum of squares. The predictors are not affected by multi collinearity (Figure 106). In sum the regression can be declared significant.
But more important is the question: Does the data fulfil the temporal aspect of vegetations trends? By using the quality criteria introduced in chapter 5.13 this hypothesis can be confirmed during the calibration phase (Figure 107).
The results show that a good agreement in the temporal course can be archived. The overall performance (Nash Suthcliff) indicates that the regression did not catch all peaks and lows.
The model validation (Figure 108) reveals that the regression reflects the temporal trend, but fails at the overall performance. One reason is the calibration of MD is focusing on the temporal gradient of the NDVI, not the overall gradient. Under that perspective the IA reflects that the temporal integrity is at a fair level.
6.5.1 Peaks and missing data inside the vegetation signal

The temporal course, e.g. EMY station (Figure 109), indicates a good statistical fitting.

![EMY Calibration& validation](image)

Figure 109 Validation of the Calibration result with a temporal extrapolation for 2007/2008 (Validation phase) for Station EMY (blue: boarder between Calibration and Validation phase)

There are some non explainable peaks and lows left inside the signal. Since they are not classified as wrong, because they are passed all statistical filters and tests, it can be assumed that this remaining outliers are taken in account but gained a low weighting during the statistical fitting. That means that the model can’t resolve a statistical dependency between those peaks and the independent parameters.
It is important to say that the elimination of outliers is done for every data pair and is therefore consistent. However, it is possible that soil water artefacts from rainfall events (which are dropped out due to missing dates from other sources (e.g. NDVI)) are included in the data because of the diminishing character of soils. A graphical interpretation of the signal shows that the predicted signal is very close to the observed signal. The difference, which can be expressed for example in the variance, is only 0.04 for the displayed figure. By keeping in mind that the signal can vary between 0 and 1 this is a very low change. But the statistical tests are sensitive to the whole spectrum (which is low here) and interpret even very low differences as significant. From this point of view a difference of 0.01 is different on a variance of 0.04 a 25%. This can also be shown in the very low standard deviation of 0.007130163 for the observed NDVI and 0.004505853 for the predicted. The general problem is that the approach lowers the signal amplitude (see Theory/Chapter5, least square effect) and therefore reactions, especially fast reactions, cannot be captured. By trying to understand the nature of these little changes it seems that there is no visible reason inside the used independent data for a reaction in the depended data (compare Figure 110). Therefore the regression can only unsatisfactorily address the reaction of the vegetation,
especially sudden peaks and lows. Also the temporal character of the signal must be kept in mind. Since most of the images are MVC it is possible that between 2 pictures there may be up to 32 days. This can have a significant statistical effect.

The second reason may be the most common land use. It cannot be excluded that some changes are due to grazing and other forms of land use. By keeping in mind that up to 90% of the vegetation productivity is grazed, it is very likely that these changes have significant influences.

Thirdly these peaks can also be due to radiometric and other failures. Therefore see MODLAND QA - Known Product Issues – Terra homepage. Especially SD_MOD13_03113 is very valuable in this context.

6.5.2 Sensitivity of individual Parameters

One of the core elements of this study is to investigate the statistical influence of meteorological data on vegetation activity. Using the explained variance of the regression provides a first result.
Figure 111 Explained Variance Independent Parameters Linear (top) and Non-Linear (bottom) Regression

Figure 111 shows that the explained variance is raised significantly during the regression approach. It is also shown that for most of the stations temperature is the dominant factor. At
the IMS station the temperature seems to have a much lower influence than ground water. This can be explained by the steepness of the area and the resulting rapid drying of the upper soil. At the TAO station the influence of all parameters seems significantly low. This is an indicator that this station is influenced by other steering parameters than the given ones.

### 6.6 NPP Results

This chapter introduces all results from Chapter 5.11 (ANPP Module). It will give an overview of the results of MD and validate it with other data sources.

RBM uses its own incoming radiation calculation, depending on latitude and longitude as well as on terrain parameters like slope, aspect, inclination and albedo.

![PAR radiation model RBM](image)

**Figure 112 PAR Radiation calculated by the ANPP module**

Calculating the radiation for all stations, Figure 112 shows the yearly distribution of PAR radiation for IMS and EMY stations as examples. The IMS station has the interesting characteristic that the direction of its IMS exposition (which is south) provides a nearly constant influx of radiation referring to a near azimuthally inclination angle. Only in midsummer the inclination angle is too steep so a little more radiation gets reflected by
albedo. The EMY station shows a typical yearly distribution on a flat area on the tropic of cancer. It is also visible that the max radiation is negligibly higher than in the IMS station.

### 6.6.1 Spatio temporal Results

![Median ANPP 2000-2008](image)

**Figure 113 Median ANPP output all stations**

The ANPP is highest for the mountainous areas, dropping down to a lower level at the basin of Ouarzazate (TRL station) and going down to a very low level in the southern part of the area. TRL is a special station with has almost dry conditions (Aridity index 0.07 (Baumann, 2009)) and a high percentage of yearly grass (e.g. *Stipa carpensis*). This result is coincident with the activity map of the Investigation area, which is calculated by the sum of activity on every pixel (Figure 114).
The output of the ANPP module shows a clear N-S profile (Figure 113) and altitude gradient (Figure 115).
This altitude gradient shows that the productivity is highest in the area around 2000 m a.s.l. By looking at the overall variance for all stations it can be shown that there is a very heterogeneous picture (Figure 115).

Figure 115 Elevation ANPP gradient
The stations with the highest mean productivities also inherit the highest variances. This must be put into perspective by looking at the temporal characteristics.

Figure 117 reveals the problem of calculating ANPP in a high mountain area. By dropping out all snowy days and data which are corrupt due to shadow effects or particular
Results of Moveg Draa

aspheric corrections problems, only the spring to fall data remains. In the case of the M’goun area data the problem of missing meteorological data in 2007/2008 can be demonstrated. If any of these data are missing the model cannot calculate a result for the time steps. For the M’goun area this means that the model has no output on productivity. By looking at the TRL station (Figure 117) it can be shown that the model also reflects a decreasing productivity. Since TRL is at much lower elevation there are less snowy days and less missing data.

[Graph showing ANPP results for the period 2001 to 2008 for the Station TRL]

Figure 118 ANPP Results for the period 2001 to 2008 for the Station TRL.

The question of Figure 118 is: Is this temporal gradient an typical annual ANPP trend? By calculating a summarized (2 events per month due to 16 days) monthly mean it can be shown that there is a clear yearly gradient (Figure 119).
TRL (as example) has a clear early spring maximum of vegetation growth and a second in late fall. The model calculates a result for every station, as long as there are data available.

One example for temperature and precipitation influences of the yearly (here 2007) gradient for temperature, precipitation and ANPP are shown for TRL station Figure 120. As expected the main peak in ANPP is in Feb/Mar. With increasing temperature the ANPP rate drops to a minimum during summer and a small peak is observed in late fall.
This underscores a trend that was already mentioned during the regression discussion. Rising temperature combined with missing rainfall tends to lower productivity.
The NDVI Biomass relationship is quite satisfactory (Figure 121). In comparison to the investigation of (Fensholt et al., 2006) it can be stated that the NDVI/ANPP relationship is difficult to handle in interannual variations, but the weighted approach minimized the problem (Figure 122).
The interannual comparison shows that the courses of both parameters is graphically very similar. The statistical key data on the other hand is relatively low (IA=0.59). By looking at the overall picture (Figure 123) this picture is much clearer.
The overall NDVI-ANPP Relationship is relatively good by looking at the coefficient of determination. The RMSE indicates indirect that the more outliers the lower the temporal agreement. This indicates that a few outliers (like seen in Figure 121) can significantly decreasing the quality of the key data. Since graphically interpretation is not objective and and some key data are sensitive to the (very low) variance (eg. IMS NDVI/ANPP relationship: 0.00081949!) it is suggested to always take normalised Indicators. For the temporal agreement of the NDVI Biomass relationship it can be concluded that the biomass model didn't react directly to greater NDVI hops, but follow the general trend of the vegetation activity course. Therefore the Biomass model must be declared stable in terms reflect vegetations lag of reaction.

6.6.2 Validation against Field Data

In order to validate the results of MD a field experiment take place (comp chapter 4.2). Using the data und the number of days the experiment lasted, it is possible to calculate a daily ANPP for MD and then compare it to the field experiment.
Figure 124 shows that the daily output of MD is close to the measured productivity. Only the TRL station underestimates the real productivity.

### 6.6.3 Influence of Cloud cover and Radiation

Several reasons lead to the decision to use a generic radiation scheme instead of a real measured one. The main reason is that the climate stations do not measure PAR. Also the net radiation instruments inherit a lot more downtimes than other instruments. Secondly the RBM model inherits a radiation routine. Thirdly, the climate scenario does not inherit PAR radiation.

Another problem is that the model works with 16 day cloudless MVC Level 3 data. The first intention to use daily data was dropped because of the required increase of computing time (16 times more) and because one intention was to use readily usable data. And, on the other hand, only cloudiness data from Ouarzazate was available. The core of the question must be this: would measured PAR radiation and/or used cloudiness data improve/impair the result? This study answers this question by investigating the uncertainty analysis by finding out if cloudiness significantly influences the outcome of ANPP model results. Since this model operates with cloud free pictures we can only say something about cloud free vegetation
activity. It should be mentioned that the direct radiation in this region is maybe stronger coupled to Mie scattering on dust particles (see (Iqbal, 1983a) p. 116f). Since no data on dust particles is available, this can only be an initial, unfounded guess.

6.6.4 Comparison to other models and temporal comparison

By comparing the results of MD to other models the problem of getting a comparable dataset occurs. As far as I know no regional biomass or productivity dataset for southern morocco exists. There are only global datasets available. Most of this dataset, regardless of the method used, inherits a global land cover for parameterization. These soil or land cover tools mainly classify most the Drâa investigation area as desert or non classified areas. This leads to the presumption that there is no vegetation at all inside these areas. (Field et al., 1995) gave a short overview on the topic of light use in different productivity models.

To demonstrate the problem results from the model C-fix (Veroustraete et al., 2002; Verstraeten et al., 2006; Verstraeten et al., 2008) have been acquired and recalculated on a monthly base.

![Graph showing comparison between monthly mean MD and C-fix for station TRL (2000-2008)](image)

Figure 125 Comparison between monthly mean MD and C-fix for station TRL (2000-2008)
TRL is chosen as representative of the first comparison station (Figure 125). The C-fix model result here inherits a zero production. The same results occur for all stations southwards. By looking at the results inside the Atlas the difference between both models become visible.

TAO ANPP monthly

Figure 126 Comparison of MD and C-fix for station TAO (2000-2008)

Figure 126 shows the main differences between both models. MD is developed and parameterized on the actual land use (since NDVI reflects that) and soil conditions. The C-Fix model is only parameterized by climate and respiration rates. C-fix therefore entails higher yearly amplitude and a clear maximum at April/May. MD has smoother yearly amplitude with two peaks in one year.
Figure 127 Comparison of C-Fix, MD and Measured Data (STE) on a Mean Daily Base (2000-2008)

Figure 127 indicates that the C-Fix model overestimates the productivity in comparison to the measured field data. It can be argued which model reflects the better temporal trend, but MD definitely is an improvement for the investigation area since it is locally parameterized to a better degree and also functions in the arid areas of the southern parts of the investigation area.

6.7 Spatial Extrapolation

Investigating the phenological cycle is a presumption to understand vegetation dynamic. Since regional or global Field experiments are very expensive or not possible, remote sensing analysis can fulfil that gap. It is possible to extract phenological parameter like length, begin, end or intra- and interannual amplitude on low cost for greater areas (White et al, 1999) by monitor vegetation activity with remote sensing sensors. Satellite born Phenology is subjective, because an objective Start and End is not ascertainable due to errors, uncertainties and other effects. The vegetation signal is a measurement on rising and falling NDVI, alternated by noise (See pre-processing and method).
Using the definition of White et al (1999), the NDVI can be described as phenological phase with Onset, green up or sequence. The extraction /derivate can be done in different ways:

- Defining limits (Adams et al., 2004) of the phenological phase, which can be over- or under run.
- gradient model (Jönsson et al 2002)
- The Harmonic Analyse or Fourier Transformation analyses the amplitudes and phases of the vegetation period in a temporal manner (Bradley et al., 2007)

MOVEG Drâa investigates the following methods:

- White, Running und Thomton (White et al., 1997b) as enhanced NDVI threshold Method
- The Fourier Analyse (Olsson & Eklundh, 1994)

Both Methods examine different Aspects of the Phenology. The threshold analyses of Phenology can produce start, end and length of the vegetation period. A Standardized Principal Components Analysis can identify potential cyclic and acyclic changes. The method of (White et al., 1997a) was investigated in the thesis of (Elbertzhagen, 2008). The method of Olsson & Eklundh (1994) will be used to introduce as method to classify the investigation area based on the intra and inter annual cycle.

"[...]every pixel in a temporal data set is a time series, showing the value of, for example, reflected light or a vegetation index, at a particular time" (Olsson, Eklundh, 1994). The amplitude and characteristics of the annual and inter-, as well as intra, annual cycle are examined by the Fourier transformation proposed by Olsson and Eklundh (1993) (c.p. also Davis 1973, Christensen 1991)

\[
f(x) = f(x)_{\text{mean}} + \sum_{r=1}^{N/2} \left( a_r \sin(2\pi r x / P) + b_r \cos(2\pi r x / P) \right) \tag{1}
\]

where:

- \( P \) = the fundamental period of the data; \( P = 12 \) for one year of monthly data
- \( N \) = the number of observation in the series
- \( r \) = the harmonic; between 1 and \( N/2 \)
- \( f(x)_{\text{mean}} \) = the mean of the whole time series

Figure 128: Fourier Formula (Source: L. Olsson and L. Eklundh, 1993: 3736)

The Fourier transformation is originally designed to extract noise from an image (Richards, 2006). It is a description of a periodic function in terms of a sinusoidal function. By use the
Results of Moveg Draa method to extract phase and amplitude functions from NDVI data, so called Harmony’s. The result of the function is the characteristics (min, max for one series) as rating for the time change inside the data set. By using the program Hants from L. Olsson and L. Eklundh (1994) a Fourier transformation is don, calculating Harmonys. Every Harmony stands for a derivation of the Fourier Transformation.

Figure 129 composite picture of the Fourier classification. The image contains 2 Levels of Information: Colormixture and Intensity. The brighter an area the higher the activity. Redish means annual constant vegetation. Green means uni-modal and blue bi-modal distribution of the vegetation signal.

The composite picture in Figure 129 shows a graphical illustration of the function with Red for mean NDVI, Green for 1st Harmony (6th on 6 year cycle) and Blue for 2nd (12th on 6 year cycle) Harmony.

Figure 130 sample Fourier functions for 2002 (source: Elbertzhagen (2008))

As seen in Figure 130, the 6th harmony can be interpreted as unimodal distribution of the vegetation period, represented by the NDVI, inside the area. Figure 130 shows also that the Fourier function phase a little in time and differs in the amplitude of the function. As shown in the priviosly chapters the vegetation inside the Atlas Mountain is on a thermal gradient.
The results of the Fourier analyses show that the higher a Harmony the better the altitude explains the vegetation activity ($R^2 = 51.83$ for 3rd Harmony). This means that short time vegetation activity changes are as expected. Finally, I compared the classification result with the existing vegetation map (Finckh, in prep.) and the derived natural units by using a confusion matrix. Therefore, the derivate classes arranged in proper order to vegetation classes and natural units map that occurs in the area.

<table>
<thead>
<tr>
<th>vegetation classification (percent)</th>
<th>natural units classification (percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class</td>
<td>unclassified</td>
</tr>
<tr>
<td>unclassified</td>
<td>99.04</td>
</tr>
<tr>
<td>9</td>
<td>0.52</td>
</tr>
<tr>
<td>5</td>
<td>0.13</td>
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<tr>
<td>10</td>
<td>0.07</td>
</tr>
<tr>
<td>2</td>
<td>0.06</td>
</tr>
<tr>
<td>total</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Figure 131 Confusion matrix for classes inside the atlas region

Figure 131 illustrates the shifts and differences inside the area. The vegetation response units get an overall accuracy of 73.96% (Kappa Coefficient = 0.6245) compared to the vegetation classification. By comparing the results with the derived natural units we get an overall accuracy of 84.01% (Kappa Coefficient = 0.74). The overall accuracy results show that our unsupervised classification characterises the area very well.

Additionally to the quantitative accuracy assessment, the result was compared graphically. The differences between the automatic classification and the manual expert classification are in the arbitrary delineation in the case of the natural units inside the area. The natural meso-units are drawn according to fundamental geologic criteria and relief parameters. Widely both appendages share the same criteria, but vegetation formation has an environmental performance indicator that is not strictly bound to river boundaries or geological boundary. As investigation inside the Drâa Catchment shown is that, the Biomass increase is significant under non-grazing conditions inside the Atlas (IMPETUS, 2003). This method allows an exact classification of spectral information given on one to three steps in time. Nevertheless, the bottom line is the (mono) temporal character of the supervised classification. The Fourier transformation gives the opportunity to classify multi-temporal vegetation response units. Those areas are usable as input classes for modelling, as we classified them as identical on climatic influences. We are dealing with two uncertainties at this point. Firstly, we do not know everything about the processes that are going on, but try to reduce them mathematically. Secondly, we try to quantify process parameters, boundary conditions and starting points through the variability of the process, but analyzing them are more than statistic (Diekkrüger, 2000).
Vegetation Response Units Classification (Figure 132) are units, which can associate with non spatial meteorological data. During the Forecast process the module access Figure 52 to determinate the Zone and Figure 132 to determinate the Regression Formula.

The result contribute to a future spatial extrapolation, by using a activity dynamic based classification. Every class can be sorted to one station and is therefore extendable to station and measurement density. Secondly the result gave an information of the usability of the area, sparse modeling computing speed and results are machine ready for further calculations. Also the lower computing steps are useable in case if you want to fast predict
an area for disaster management. This advantage, especially in developing countries, is crucial because of the lower computing power.
6.8 Forecast Results

This chapter presents the results of the forecast module. It first uses the regression formula generated in Chapter 5.10 and applies it to the climate data described in chapter 5.14 by using the two different scenarios A1B and B1 of IPCC. In a second step the results are used together with the ANPP module described in chapter 5.11.

6.8.1 NDVI Prediction

The future climate dates, described in Chapter 5.14, are now used together with the regression built up in Chapter 5.11 of the NDVI to calculate the NDVI from 2001 to 2050.

![Figure 133 Prediction of NDVI (y-axis) for Station EMY with Scenario A1B and B1 as daily forecast and Box-Whisker statistical overview](image)

As seen in Figure 133, the results for both scenarios indicate that the plant activity decreases slightly, including some outliers. These are dry years (model data) or real outliers due to an overfitting of the regression model. On the right side the box plots for the displayed time are shown. The variances are very low. And the visual numbers of outliers are very few, due to the amount of data. This is done for every station used and for both scenarios.
6.8.2 Dominance results of the long forecasting module

One of the first things to be calculated with the NDVI data is the dominance or total vegetation cover. The variation coefficient shows that the ground cover varies up to 30 % (not displayed).

![Figure 134 Forecast of dominance for Station EMY (y-axis) with Scenario A1B and B1 as daily forecast and Box-Whiskar statistical overview](image)

The displayed dominance in Figure 134, e.g. for station EMY, is integrated into the ANPP calculation. For EMY station it can be shown that the mean ground cover decreased over the time of the projection. This occurs on a very low level.

6.8.3 ANPP Results

Using the RBM module, as in the ANPP calculation for 2000 to 2008, the calculated NDVI values are used to calculate the productivity based on the climate data from the IPCC scenarios A1B and B1.
Figure 135 ANPP Forecast for IPCC scenario B1 for all stations (Units in g/m²/day)
Figure 136 ANPP Forecast for IPCC scenario A1B for all stations (Units in g/m²/day)

The Figure 135 and Figure 136 shows the daily calculated ANPP for all 9 Stations used in this study. In general it can be stated that the vegetation productivity is changing on a very
low level. This slow change is consistent with the results from Finckh (oral). Secondly the yearly (annual) and interannual cycle can be shown and used for further studies.

**Scenario A1B**

![Graph A1B](image)

**Scenario B1**

![Graph B1](image)

Figure 137 decade mean long term trend of ANPP for all stations (daily ANPP)
The long term trend can be illustrated by the long term change mean (Figure 137). The changes occur only on very low levels for both scenarios. It is visible that the mountain stations (TZT to TAO) are on a stable, sometimes slightly increasing level. The stations BSK to JHB are also stable, albeit slowly decreasing.
6.9 Uncertainty Analysis

This chapter investigates in which way errors influence the results and on which magnitude said results are influenced. Uncertainty analysis in complex models is a necessary step to evaluate if the model is stable, and under which conditions. This can also be seen as a sensitivity analysis, but with the exception of summing up the input parameters.

![Uncertainty Analysis](image)

The starting point of uncertainty analysis is the presumption that the full parameterized model rightfully describes the analyzed processes, as long as data is available (Diekkrüger et al., 2006). Input uncertainty is a result of errors in input data such as rainfall, and more importantly an extension of point data to large areas in distributed models. As errors can have a structural model or parameter source, the uncertainty in physically based process models is normally smaller than in conceptional models (Giertz, 2004). For all models the following applies: The more input parameters, the more uncertainty (Giertz, 2004; Refsgaard, 1997). This chapter describes in which way and under which conditions the uncertainty analysis takes place.

6.9.1 ANPP Uncertainty

The uncertainty analysis for the ANPP module is done in three steps. Firstly those parameters are identified that are equable for an uncertainty analysis. Secondly the parameters are tested for consistency and model stability (parameter sensitivity). Thirdly, uncertainty limits for every parameter are set.

The result is an output for all investigated cases. By taking limits on the 0.025 and 0.975 percentile on the results a p-value of 97.5% of all values is acquired. This excludes extreme parameters and the percentiles give a better impression of the occurrence frequencies than other methods e.g. mean.
This following data is subject of a possible uncertainty analysis:

- CN2 (Runoff Curve Number Parameter)
- Total Ground cover
- C/N coefficient
- Field capacity
- Cloudmask

The Curve Number (cn2) is taken as the parameter which determines the amount of water that can be held inside a soil profile. As parameter of the runoff, it is a quite an important parameter to plant water availability (Cronshey et al., 1986). For this study the soil characteristics are altered on the mean in a variation of 4 points. That essentially means that we influence the infiltration and runoff by ~8%.

As described in chapter 5.10 a regression approach for calculating ground cover, on base of the NDVI, is used. For testing uncertainty on this parameter it is assumed that the approximated ground cover, determined during fieldwork, is slightly of scale. Therefore it is altered by a normal distributed value with a mean of 0 and a 4 standard deviation width based on the measured ground cover. This generates a measure error of up to +- 15%.

The C/N coefficient is a valuable parameter for describing plant nitrification. Under the presumption that this parameter is not estimated correctly and may change (Cronshey et al., 1986), an altered value on a normal distribution with a mean on the specific station is generated.

The field capacity is a factor on how much water, and therefore how long, is stored inside the soil profile. The field capacity is provided by Löose (2009). The field capacity is not constant and is in fact changed by many factors. By approximating that changes are continuous and occur in both directions, and that measurement errors can go in both directions, a mean for every station is taken and altered on a normal distribution with a deviation of 4 standard deviations.

Cloudiness is important in terms of the input energy into the system (Iqbal, 1983a; Richters, 2005a). Since RBM uses a linear function using the extinction coefficient to calculate the PAR irradiation the parameter is very sensitive. Since cloudiness is randomly distributed (see chapter 5.11) a uniform distribution is chosen (and therefore near random) to simulate the cloudiness between 0 to 100%.
The factor of carbon fixing was not included because this factor is bounded too close to radiation, and a high collinearity is taken. Secondly the low quantity of data does not allow a founded choice of an alternating level. The factor radiation is covered by cloud mask.

The firstly analyzed parameters are the RCN and CN2 parameters. Both parameters don’t affect the final result due to the effect that arid soils rarely reaches their potential water capacities (Simmar, 2003) and therefore the effect tends to be zero. The same goes for saturation runoff. Only very low profile soils and very humid months in higher areas are capable of saturation runoff (eg. Mountain ridges). Because of the rare occurrence this factor is dropped on further analyses, but kept in the model for two reasons. Firstly it is a good quality parameter for the soil module. Secondly it enables the model to work in higher mountain areas und prepares for other working areas.

The selected Parameters (Table 9) can be declared independent.

<table>
<thead>
<tr>
<th>Table 9</th>
<th>Correlation matrix of Input parameters Uncertainty IMS Station</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground_Cover</td>
<td>cncoef</td>
</tr>
<tr>
<td>Ground_Cover</td>
<td>1</td>
</tr>
<tr>
<td>cncoef</td>
<td>-0.00364806</td>
</tr>
<tr>
<td>CLOUDMASK</td>
<td>0.0245299</td>
</tr>
</tbody>
</table>

The Uncertainty Parameters can be graphically displayed (Figure 139).

These are the uncertainty assumptions.

6.9.2 Sensitivity of the selected Input parameters

By using these three parameters the uncertainty analysis takes place by combining the Monte Carlo Analysis with the Latin Hypercube Method of (Diekkrüger et al., 2003). An
uncertainty dataset for each parameter is created including 3000 combined iterations. The result is calculated and analyzed by calculating the three percentiles (0.025, 0.5 and 0.975) and graphically plot them. In a further analysis the 0.5 quantile is compared to the values of the original calculated ANPP.

6.9.2.1 Cloudiness

Using the 3000 iterations it is possible to reveal the influence of cloudiness on the productivity of the model.

![Uncertainty Cloud cover influence (2000-2006)](image)

Investigation of the cloud cover influence reveals that for every station a maximum productivity can be calculated which shifts to slightly higher cloud coverage in the north. Secondly it can be shown that the model slows down the productivity at a cloud cover of around 55% to a minimum. This can be explained by the fact that a cloud cover over 50% is never used during the parameterisation of the model and the productivity below that points is not exactly 0. It is more that the model asymptotic goes to a minimum.
6.9.2.2 **Ground Cover**

The ground cover is an important quantitative parameter for estimating the density of vegetation that is on an area and influences the productivity of the area (comp. Chapter 6.6).

![Uncertainty Ground cover error](image)

**Figure 141 Uncertainty Ground Cover error**

The uncertainty in ground cover shows that there is a linear relationship for ground cover influence on ANPP. The ANPP values of 0 are due to the fact that the calculated ground cover was capped at 0 to prohibit a negative total ground cover.

6.9.2.3 **Carbon to Nitrogen coefficient**

The C/N coefficient is one of the most important factors to measure plant nutrient supply.
The C / N uncertainty relationship shows that productivity is in a hyperbolic relationship. All values above a c/n of 25 are negated by the model. This uncertainty reveals also that the highest productivities are on a lower level than the actual value. A lower level means that the nitrate availability increases. This in turn means that for the two displayed soils N is not optimal. It can therefore be stated that nitrate is at a minimum of plant productivity in the system.

### 6.9.3 General uncertainty

Using all uncertainty parameters together, a general uncertainty can be calculated for every station from 2000 to 2006 (Figure 143).
Figure 143 shows that uncertainty can be at a relatively wide value between 40 to 100 % around the original value. The lower level is always 0 because zero productivity is always possible. The upper limit is a given upper limit of the model for all possible influence combinations.
This high variation of up to 100% is not quite satisfactory, but the 0.5 quantile is quite lower than the normally calculated ANPP (Figure 144).

Figure 144 ANPP and 0.5 quantile comparison

This is an indicator that most of the calculated values are below the calculated ANPP or quite small. This is also an indicator that the productivity can be much lower in certain circumstances. In summary the ANPP can be displayed by its calculated value and the error bar provided by the uncertainty analysis.
By taking the mean difference between the 0.5 quantile (which is the median value in this case) of all calculated values and the calculated ANPP from the model driven by the measured values, a near symmetric distribution of errors in negative and positive direction can be stated. This means that the model entails a nearly 100% variety in both directions. Figure 143 demonstrated that this can go up to 500% for extreme combinations. This extreme variety is due to the relatively low numbers.
7 Conclusion and Discussion

Modelling is a game, but it is a serious game (Beven, at the 2001 EGS conference in Nice).

Core objective of this study was the interdisciplinary approach of analysing vegetation activity on the base of satellite and meteorological data. Therefore the vegetation course for the years 2000 until 2008 inside the Drâa valley was investigated by using NDVI Data in order to understand the principals of vegetation dynamic. Nine corresponding climate station data was analysed to investigate the climatic situation. The main challenge of this research has been to unite diverse scientific disciplinary approaches to develop a model that can provide a robust semi-automatic analysis of vegetation dynamics including most vegetation relevant environment parameters for the semi arid region of the Drâa Valley in southern Morocco. By using sophisticated mathematical approaches the results show it is possible to analyse and simulate natural processes on the basis of their dependencies. This final chapter will conclude all results from chapter 6 and 7.

7.1 Regression approach

These studies show that the vegetation activity mostly depends on temperature. It can also be shown that the temperature goes from a positive correlation inside the Atlas mountain area to a rising negative relation in the south. This shows that with rising temperatures (positive correlation) the vegetation starts to react and with temperature above a certain level the NDVI declines. This also seems to highlight the models problem in higher mountain areas of capturing vegetation activity, especially in winter. Since we already sort out temperature below 5°C, the vegetation growth seems too unsteady. This model was tested on its quality behaviour and in a split sample test for calibration and validation.

The low level soil water content (in comparison to the total water capacity) corresponds to long lasting water stress. Combined with often high water vapour pressure deficits, arid plant life has adapted by creating mechanisms against water loss (Lajtha & Whitford, 1989; Snyman, 2005). The original thesis that only rain is the steering factor for plant growth must be rejected and replaced by a rain steered water pressure deficit minimisation in a plant physiological sense. This means that rain minimizes temperature and decreases the water vapour deficit, due to which said reason temperature inherits greater explained coherency. This doesn’t change the fact that rain, or general water availability, is a prerequisite for plant activity. More water doesn’t effectively mean more nutrification (comp. (Lajtha & Whitford, 1989; Snyman, 2005). In this context it is not surprising because plant physiology is in the balance of energy gains and energy losses (see Baumann, 2009). More rain doesn’t mean more nutricants, and this in turn means that the physiological reaction is slowed down. And
the other factor, that of extensive evaporation, is also involved. A possible improvement can be achieved by introducing a more detailed investigation between usable nutrificants and soil water content. This is not included here because there is no detailed study on this topic for this area.

**7.2 Biomass**

The ANPP module calculates the highest production rates inside the high mountain Atlas range. This is comparable to the results of (Baumann, 2009) and other data sources.

As for pastoral use the grazing value is not only determined by high production of forage, but the predictable availability of forage (Baumann, 2009), its most important to forecast the seasonal production. As shown in chapter 6.6 the that forecast can be done on a reliable basis. The model is stable (comp. Chapter 6.6. and 6.8) and reflects the annual and interannual course without following hops of the input data. This is remarkable since the ANPP model has now kind of memory. MD is therefore optimized on the mid to long term prediction.

Since nomads and their herd’s use surplus of vegetation, the vegetation signal is dampened by higher use and amplified by lower usage. This may explain some outliers that are inside the activity data. If one area is not used during one time the signal may be outlining because of that effect.

It is always a problem to transfer NDVI and NPP results to other areas or to use other sensors. This will always come with high failure rates and under or overestimation (Menz, 1996). Typical problems that can be lead to over or underestimation are

- Non-consistent measurement (shifting of stations, change of Sensors)
- Non-sufficient pre-processing (pixel location, radiometric shifting, cloud influences)
- Possible under-, overestimation of standing crop and NPP in field measurement
- Mathematical problems due to applying regression results on an area with a high wood content

This study avoids these problems by using a defined product and a semi-automatic approach which is self-adjusting with new data. Based on the work of (Diouf & Lambin, 2001) this investigation firstly discusses the issues of climate variability and prepares it for automatic modelling.

The comparison with other models (comp. Chapter 6.6.4) reveals that MD has a lower yearly amplitude, but on overall a better parameterisation of the mean daily productivity. The great advantage of MD is the individual parameterisation for the whole Investigation area and the possibility to integrate more data. This open standard is an advantage for transferring the
model to a greater area or other areas. (Richters, 2005a) also mentions that a scaling on higher resolutions will in general improve the possibility to describe and identify more structures on a small scale. This is done by MOVEG DRAA by improves the spatial resolution by factor 16. The discussion of primary production is interwoven with the carbon fixing discussion. Carbon fixing is coupled with significant sinking of carbon dioxide (Schimel, 1995;IPCC Working Group3, 2001) and the role of vegetation inside the global cycle. Primary productivity is more concerned with the roll of vegetation depending on energy provided and used by plants (Le Houérou, 1984;Oke, 2003). (Monteith, 1972;Monteith, 1965) goes one step further by bringing aspects such as the efficiency factor into the discussion.

The greatest advantage of MD is that it can improve the spatial understanding by integrating data of a long time series, which is hard to survey by other means. This is something which can typically only be provided by remote sensing data. By using a modular structure all options for extensions are wide open. MD is a self calibration, semiautomatic model which

- Test the input parameter with an automatically Error handling
- Self assimilation, depending on the combined length of all input factors
- Self calibration, depending on condition given by input parameter.

### 7.3 NDVI forecast

The long term forecast of the model is a bit static in terms of the long term trend (comp. chapter 6.7.). This is an indicator that the long term relationship of NDVI / atmosphere is not fully explained by the model. This is partly due to the modelling strategy (see least square problematic in Chapter 5.10) and partly to the MVC composite. The MVC composite problematic can be viewed as a problem of brightest glowing. Ultimately, MVC means that pixels of brightest value (eg. greatest value) are taken. Under the assumption, and this is not always true, that the brightest signal is also the date of its neighbour, it can be assumed that there are pixels in neighbouring different states. This can cause unexpected spatial shifting. One of the main problems in this work is that the real day of the MVC NDVI measurement is unknown. This can raise the problem of temporal unsteadiness, because two time steps can have a range between 1 to 31 days. Therefore only one value of meteorological measurement for that period can be associated with one time step.

### 7.4 Summery

This study raises the frequency of vegetation monitoring inside the Drâa catchment from a few observations by hand to a every 16 days observation by increasing the timespan to 8 years by using MODIS NDVI time series. Supplemented by a vegetation monitoring network and 10 years of measuring meteorological network a entire usable phenological database
was created. Furthermore this study also takes the impact of soil water as a main water source during draught into account. It also considers the time delayed reaction of plant activity after rainfall events. MOVEG Drâa provides a robust analysis of the phenological cycle with a robust productivity output and allows out long-term predictions based on the basis of the IPCC scenarios.
8 Outlook

This work closes the link between the lower atmospheric situation and the depending vegetation activity. One of the mayor problems will be the extrapolation of point data for an area. Especially small meteorological events (like thunderstorm events) can cause great differences in spatiotemporal measurement. Therefore remote sensing imaging sensors can spatial fill the gap between climate stations, although they cannot completely substitute them (Remsberg, 1994; O’Donnell et al., 2000). Future sensors will increasly close this gap. Sensor combinations, like NASA A-Train, future meteorological platforms like MTG (Meteosat third generation) mission and environmental missions like the LDCM (Landsat Data Continuity Mission mission (Figure 146) will substantial contribute to this goal.

The IMPETUS projects aims to provide the availability of water. Answer questions such as in which way a better management of resources can improve the quality of life for land users. Since one of the main extensive land use in southern Morocco is extensive pastoralism (comp. (Baumann, 2009; Kemmerling, 2008), a major improvement would be the combination with land use models. (Richters, 2005a) already mentioned that one of the primary extensions of the RBM approach should be to include the sustainable survey grazing. This should close the gap between production and consumption. Since the survey inside the Drâa catchment is not available, it is not possible to close that gap. One of the most important things is that the production calculated by this model is the real production minus the biomass used up by grazing. As (Baumann, 2009) mentioned grazed biomass can make up to 90% of all consumption (Figure 147).

The model itself is fixed on this grazing rate, because it includes the carbon fixing rate of the grazed area (which includes the grazing loss). It is therefore possible to give a productivity potential, but since the grazing rate is still unknown this will for now remain a hypothetical number. Modelling reaches its limits at this point.
Figure 147 Experimental measured Biomass loss due to grazing influences on 4 stations along a S-N gradient, which is also a altitude gradient. (Source: Baumann, 2009)

Figure 148 explained that the total number of sheep and goats has been rising in the last 20 years, including all the problems that come along with that fact.

Figure 148 Sheep and Goat development in morocco (Source: Service d’elevage)
As an example, the increasing trend of sheep population increases pressure on useable biomass very likely. Since the ecosystems are in transition between a degraded state to equilibrium state of transition (Finckh & Oldeland, 2006; Finckh & Staudinger, 2002; Finckh & Oldeland, 2005b) more, and finer, vegetation information are needed. Newest studies indicate that the eg ANNP is a poor indicator for degradation in this highly variable landscape (Baumann 2009). Therefore it is important to improve the carbonisation parameterisation with land use (models) and further investigations on plant growth (increasing part) and pastoralist science (decreasing part). (Finckh et al., 2009) states that the long term shift in vegetation composition gains in importance and desertification is more likely caused by firewood cutting and overgrazing. Using this regression result it can be stated that under the land use during the parameterisation phase (2000-2008) and under the climatic changes of the climate model, only minor changes in vegetation activity will occur in both scenarios. This is only a generalized output in terms of vegetation composition, but it inherits the conclusion that for ANPP calculation the general productivity change is only minor.

MD introduced a new toolset to handle low and unsteady Vegetation activity investigation on a regional scale. Its contribution of tools is set, but certain parameters undergoing a further development by improving space technologie. It is most certain that remote sensing in all scales will be constantly increasing it’s contribute to earths observations and the benefit it provides to the understanding of the interactions inside all processes on earth.
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