HYECO'04: USING HYPERSPECTRAL REFLECTANCE DATA TO INITIALISE ECOLOGICAL MODELS

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ABSTRACT

We conducted an exploratory study to determine the usefulness of hyperspectral data for the initialisation and validation of ecological models. To this end HyMap images were acquired in a floodplain area in the Netherlands. Simultaneously we determined the biomass of the vegetation by clipping and weighing, and we related biomass to reflectance using LAI as an intermediate variable. We simulated vegetation development with the ecological model SMART - SUMO, using timesteps of one year and starting with the estimated biomass in 1975. We compared the biomass simulated for 2004 with the measured biomass. Next we attempted to improve the performance of the model by re-initialising it in 2004 using the biomass estimated on the basis of the HyMap images.

INTRODUCTION

The preservation of biodiversity is an increasingly important topic in European policy. Natural areas are constantly undergoing changes, mostly driven by socio-economic factors, and many of these changes lead to a reduction of the biodiversity. Such a reduction in biodiversity may be caused by e.g. pollution, habitat loss, atmospheric deposition or climate change. Often dynamic models are used to evaluate the effectiveness of measures intended to counteract biodiversity losses (i, ii, iii). In the Netherlands the coupled soil-vegetation model SMART-SUMO is used to predict long-term effects of scenarios that entail e.g. pollution abatement or changes in management on a national scale (ii, iv). An important constraint in the application of dynamic models is their strong need for geographically explicit input data. Such input is required for both initialisation (i.e. to provide the model with values for its state variables at t=0), and validation (i.e. to confront model output with actually measured values). Both initialisation and validation of the models has so far only been carried out on the site level, based on anecdotic information (v). Hyperspectral imaging spectroscopy has the promise to provide the data required for model calibration and validation in a continuous field (vi). The present paper presents a case study where we attempted to use data derived by hyperspectral imaging spectroscopy for calibration and validation of ecological models.

Models

The model SMART-SUMO is used to simulate vegetation development under scenarios of changing abiotic conditions and management. SMART (vii) is a soil chemical model that describes chemical processes like weathering, adsorption, desorption, mineralisation and immobilisation. SUMO (ii, iv) describes plant competition and resulting vegetation succession. It breaks down the vegetation into five functional plant types (herbs and grasses, dwarf shrubs, shrubs, pioneer trees, climax trees) that compete for water, nitrogen and light. Vegetation is characterised in terms of biomass (in $t.ha^{-1}$) and height per functional type. The combination of SMART and SUMO contains a full description of the nutrient cycle through root uptake, investment in biomass (divided over root, shoot and leaf), litter fall and mineralisation. Fertilisation and atmospheric deposition of nitrogen compounds are also accounted for. Vegetation management (e.g. mowing) is described as the removal of part of the biomass at the end of the growing season. Both models have a time step of one year, i.e. the simulated biomass is the maximum standing biomass in each year.

SMART-SUMO is a point model, i.e. it does not describe spatial interaction. Therefore the model can be applied on any spatial scale provided the necessary input data are available. Important inputs for the initialisation are e.g. biomass and leaf nitrogen content. For applications on point level these inputs can be directly estimated or measured, but for a nationwide application such data are not available, and have to be derived indirectly from various sources e.g. topographic maps or vegetation maps. The absence of reliable data for initialisation and validation contribute to a large extent to the uncertainly of nationwide applications of dynamic models. In the present study we explore imaging spectroscopy as a method to make geographically explicit estimates of biomass, which we subsequently use to both validate and initialise the SMART-SUMO model. We did this for a single test site, so that biomass could be validated on field measurements. However, we expect that, if this procedure is sufficiently elaborated, it can be upscaled to the national level and thus significantly decrease the uncertainty in the model output.

Test site

Our test site is part of the nature reserve 'Gelderse Poort', located in the valley of the river Rhine near the Dutch - German border (Figure 1). The site was in agricultural use until 1993. After that date natural succession was allowed to proceed. Grazing takes place by horses and cattle in a low density, allowing a highly varied vegetation to develop, from sparsely vegetated river shores through grassland and scrubland to forest (viii, Figure 1). It should be noted that grazing intensity is highly unevenly distributed over the total area, leading to locally very shortly grazed vegetation, and scrub development in other parts.

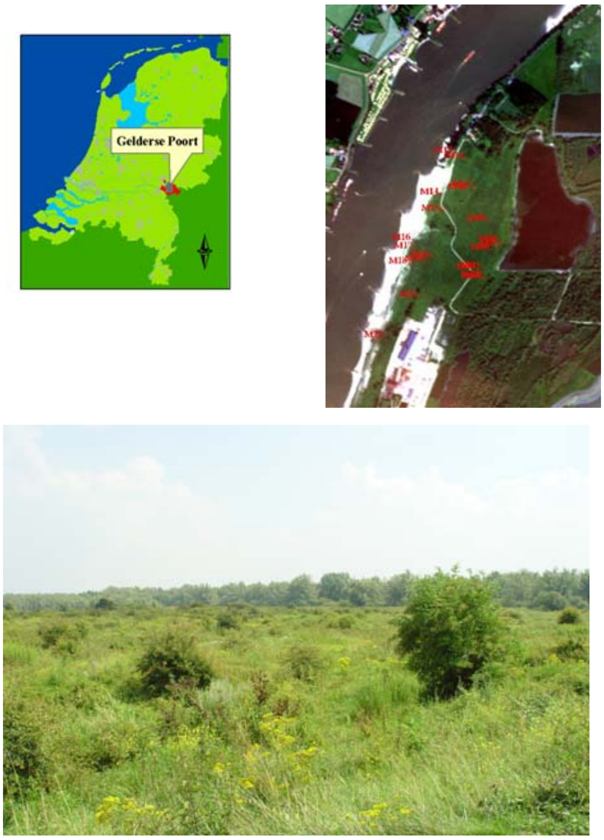

Figure 1: Location and overview of study area (numbers indicate the locations of the plots).

MATERIALS AND METHODOLOGY

Data acquisition: ground observations

We selected 21 plots measuring 2X2 m, covering the most important vegetation types present in the area except the forest. In these plots vegetation relevés were made according to the method of Braun-Blanquet (ix), and biomass was determined by clipping, drying and weighing three 50X50 cm subplots. Top-of-canopy reflectance was measured using a Fieldspec FR instrument (Figure 2). A hemispherical camera was used to determine LAI in the forested part of the site (x, xi). Further details are given by Kooistra et al. (xii).

Data acquisition: hyperspectral images

HyMap images were acquired on July 28 and August 2, 2004 in 126 bands from 400 to 2600 nm (bandwidth 15 - 20 nm). Top-of-canopy reflectance and reflectance of reference surfaces (open sand, clay, water, and asphalt) were used for radiometric correction. Details are given by Kooistra et al. (xii).

Data processing

To retrieve biomass from hyperspectral data we used a quantitative statistical and semi-empirical approach, with LAI as an intermediate variable. Here we define LAI as one half of the total leaf area per unit ground surface (xiii). We used the Reduced Simple Ratio (RSR) to derive LAI according to the algorithm proposed by Chen (xiv; see also (x)):

$$RSR = \frac{\rho NIR}{\rho RED}\left(1 - \frac{\rho SWIR - \rho SWIR\min}{\rho SWIR\max - \rho SWIR\min}\right) \qquad (1)$$

where RSR, Reduced Simple Ratio and ρNIR, ρRED and $\rho SWIR$ are the reflectance in NIR, RED and SWIR bands, respectively. $\rho SWIR\min$ and $\rho SWIR\max$ are the 1- and 99-percentile of the SWIR reflectance found in the HyMap image of the Millingerwaard. The vegetation of the Millingerwaard consists of a mixture of grassland and deciduous shrubs (*Rubus* spp., *Crataegus* spp., *Sambucus nigra*). We used the transition formula given by Chen (xiv) for ‘deciduous forest’:

$$LAI = -3.86\ln(1 - RSR/9.5) \qquad (2)$$

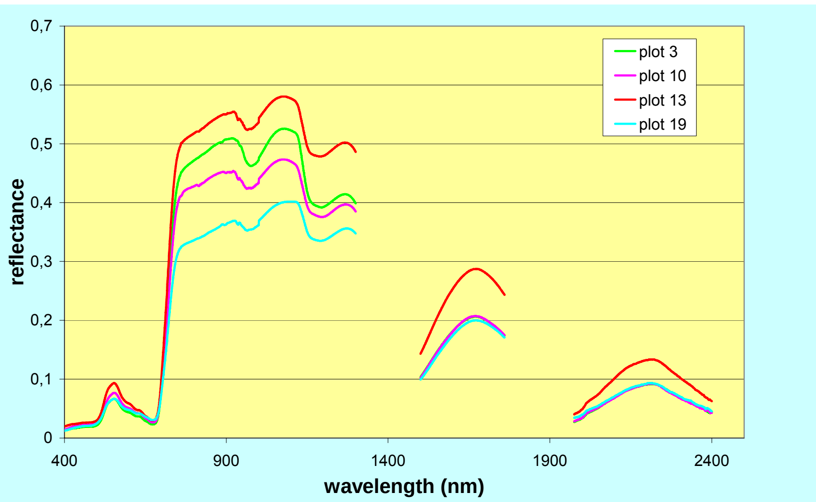

Figure 2: Examples of top-of-canopy reflectance for four plots (plot 3, Echio-Melilotetum typicum; plot 10, Artemisio-Salicetum; plot 13, Dauco-Melilotetum; plot 19, Bromo inermis-Eryngietum campestris).

In the analysis of this case the reflectance data of HyMap spectral bands 15 (650 nm) and 28 (846 nm) and 82 (1661 nm) were considered for RED, NIR and SWIR bands respectively. The LAI derived from hyperspectral images was validated for the forested part of the test site using hemispherical photographs (see (x) for further details). The biomass determined for the plots by clipping and weighing was regressed on the LAI derived from the HyMap images for the corresponding pixels.

Model application

To initialise SMART-SUMO we assumed standard biomass values for country-wide applications of SMART-SUMO for both agricultural and natural grassland in 1975. We used two scenarios to evaluate the effect of agriculture: a continuation agricultural management i.e. yearly mowing, and natural succession under grazing. For the present application we assumed the hydrology to be constant over time, with a low phreatic level. The soil type (sand or clay) was derived from field observations made in the plots. Also the local cattle density in the 'natural' scenario was estimated from field observations in the plots. To validate the model we compared the simulated biomass in 2004 under the natural succession scenario to the measured biomass in the plots. Next, we attempted to improve the simulation under the 'natural succession' scenario by replacing the simulated biomass of the 'grasses and herbs' functional type in 2004 by the biomass estimated from the HyMap-derived LAI, and running the model for another 45 years (i.e., until 2050).

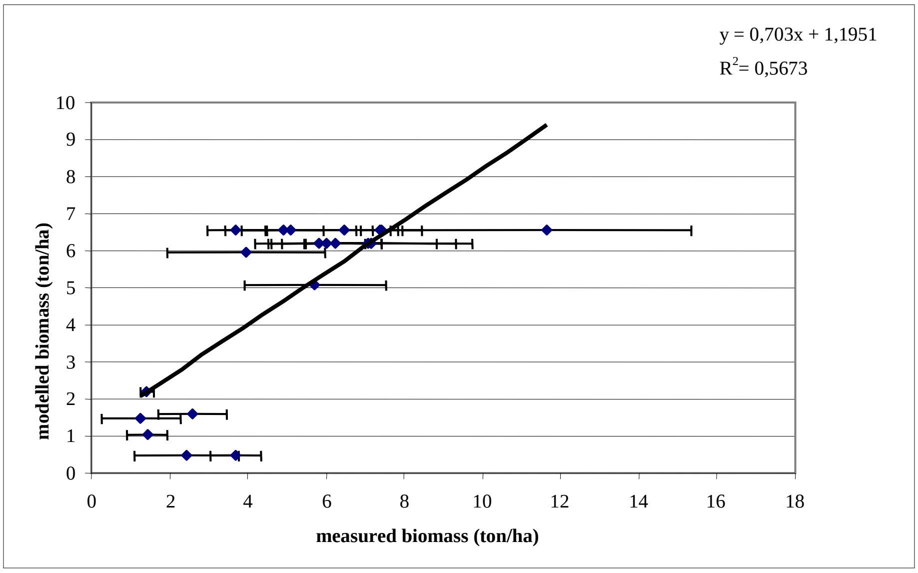

Figure 3: Measured versus modelled biomass. Modelled biomass are values taken for 2004 from the SMART-SUMO run for 'natural succession', measured values were determined by clipping and weighing.

RESULTS

Figure 3 shows the validation of the biomass simulated by SUMO for 2004 on the biomass measured by clipping and weighing. There appears to be a good agreement between the measured en modelled biomass, although at very low biomass the simulated values are sometimes significantly lower than the actually measured ones. This may be due to an over-estimation of the grazing intensity (note that the plots with low biomass values are the grazed ones).

Figure 4 is the LAI image of the area derived from the HyMap image using Eqs. (1) and (2). Figure 5 gives the relation between the measured biomass and the biomass derived from the HyMap image for the pixels containing each plot. There appears to be a significant linear relationship between the HyMap-derived LAI and the biomass (r^2 = 0.61) when excluding the grazed plots.

Finally, we attempted to improve the biomass simulated by SUMO for 2050 by re-initialising SUMO in 2004 using the HyMap derived biomass. Figure 6 shows the result for two scenarios: continuation of the agricultural management and natural succession; the latter with and without re-initialisation in 2004.

DISCUSSION

Our results show that remotely sensed information can be used for initialisation of ecological modes. In this exploratory study we relied on existing concepts i.e. the relation between RSR and LAI using the parameter values found by Chen (xiv). For the purpose of the re-initialisation of SUMO we determined the relation between LAI and biomass by linear regression. We used LAI as an intermediate variable because more data were available for its validation (xi). A more straight-forward approach would be to derive biomass directly from hyperspectral data e.g. through the relation between biomass and vegetation indices. As these relations are established empirically and differ per vegetation type (like LAI), more field data would have to be acquired, covering a range of vegetation types. A differentiation could be made between vegetation types according to their dominant functional type e.g. herbs and grasses, shrubs or trees.

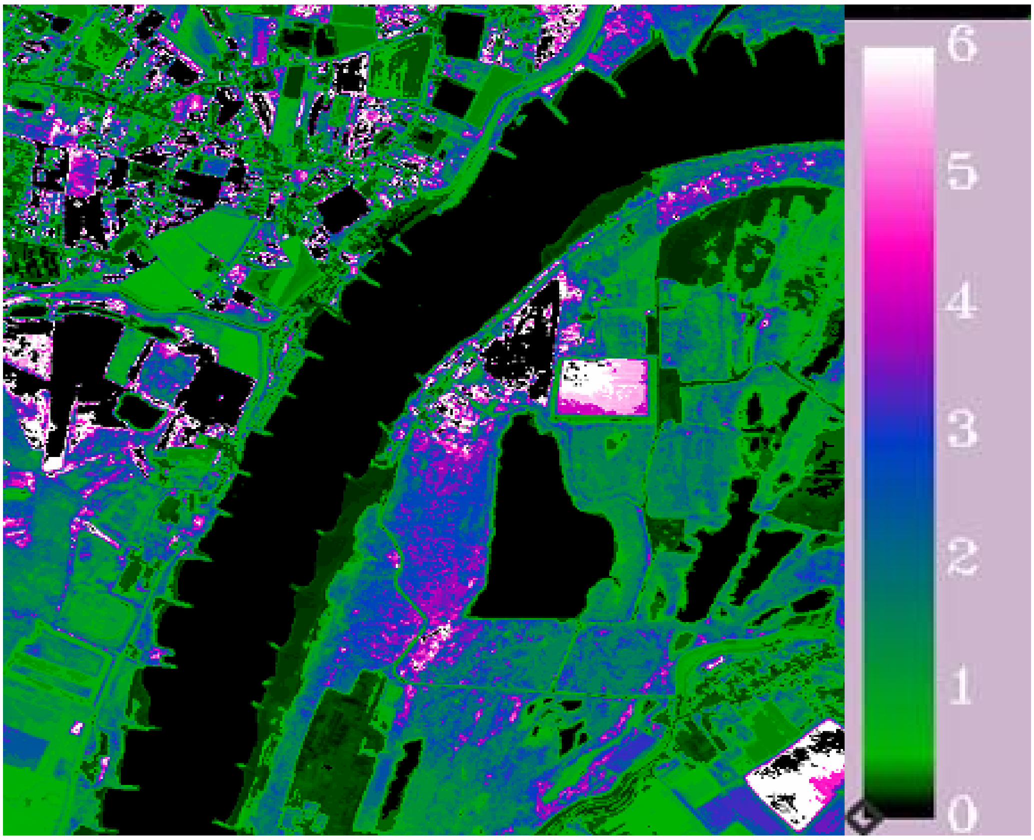

Figure 4: LAI image of Millingerwaard based on Eqs. (1) and (2).

Figure 5 shows that grazing also influences the relation between reflectance and biomass: the grazed plots appear to have a much higher LAI (so apparently, a much higher RSR) at a given biomass compared to the ungrazed ones. These plots were excluded from our analysis because their low number prevented a separate calibration. An explanation for the high RSR of the grazed plots might be their N-content; a chemical analysis of plant material showed that its N-content was significantly ($P<0.001$) higher in the grazed plots (2.0%) than in the ungrazed plots (1.3%). For other nutrients (P, K, Mg) theses differences were not significant. Apparently management (e.g. grazing, mowing) will also have to be taken into account if biomass is to be estimated from reflectance.

If biomass can be estimated over time it becomes possible to use remotely sensed data for the validation of ecological models. In our study such data are not yet available, and the performance of the model in predicting the temporal development can only be judged by expert knowledge. After re-initialisation, the increase in grass + herb biomass over time becomes less, while the woody biomass increases more rapidly. This seems to agree better with the actual vegetation development in the area, where scrub cover rapidly increases at the expense of grass cover (xv).

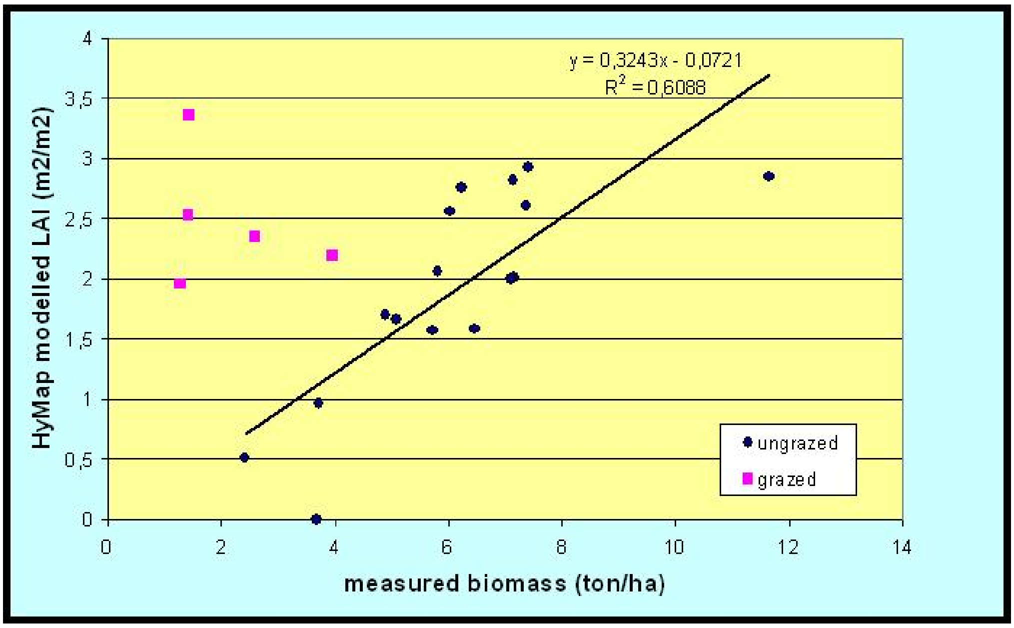

Figure 5: Measured biomass for the plots vs. HyMap derived LAI derived for the corresponing pixels using Eqs. (1) and (2). The regression line pertains to the ungrazed plots only.

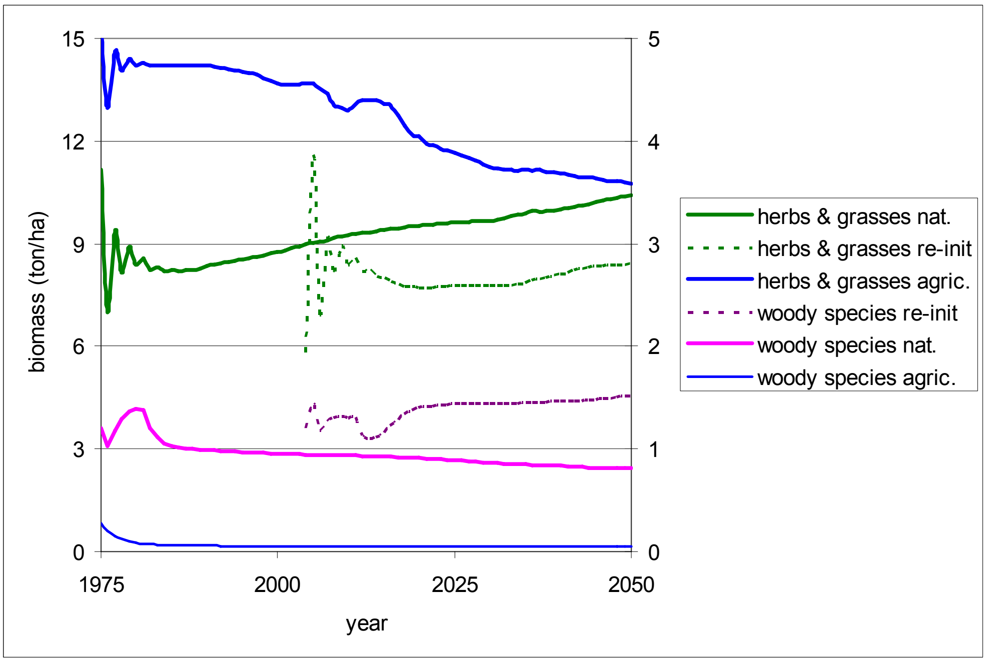

Figure 6: Biomass simulated by SUMO for two plant functional types, under a scenario of fertilisation and grazing ('agric') or natural development ('nat'), the latter both with (dotted) and without (drawn) re-initialisation in 2004 ('re-init'). For the 'herbs & grasses' functional type the re-initialisation was based on HyMap data. The left vertical axis gives the biomass of the herbs and grasses, the right vertical axis gives that of all other functional types. The start of the dotted lines is the re-initialised value. The oscillations in the first years after (re-)initialisation are due to model instability.

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