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Assessing and predicting biodiversity in a floodplain ecosystem: Assimilation of net primary production derived from imaging spectrometer data into a dynamic vegetation model

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Abstract

New concepts for river management in northwestern Europe are being developed which aim at both flood protection and nature conservation. As a result, methods are required that assess the effect of management activities on the biodiversity of floodplain ecosystems. In this paper, we show that dynamic vegetation models (DVMs) in combination with regional scale derived remote sensing products can be adopted to assess both current and future ecosystem development and biodiversity status of a complex floodplain ecosystem in the Netherlands. The dynamic vegetation model SMART2-SUMO2 in combination with the nature valuation model NTM3 predicting potential floristic diversity was applied to simulate the biodiversity status of the Millingerwaard floodplain along the river Rhine in the Netherlands. Estimates of net primary production (NPP) derived from airborne HyMap imaging spectrometer data were used for validation of the simulated NPP by the DVM at the time of data acquisition in 2004. Imaging spectrometer derived NPP was in good agreement with the SMART2-SUMO2 modeled results. The NTM3 derived nature valuation in 2004 expressed as plant diversity for the floodplain was high and well in agreement with field observations. In a next step, the DVM was re-initialized using imaging spectrometer derived NPP in 2004 and a forecast of plant diversity and biomass development in 2050 was made. A comparison was performed for three pre-defined floodplain management scenarios using a data-assimilation based approach as well as one without. Significant differences in biomass development can be observed between the scenarios. Predicted plant diversity for individual ecosystems in 2050 shows increased variability for forest ecosystems compared to grass ecosystems. This shows that floodplain management should take advantage of spatiotemporal dynamics of the floodplain as a basis for fostering the development of increased biodiversity. The results of this study demonstrate that imaging spectrometer derived products can be used for validation and initialization of DVMs.
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Keywords: Dynamic vegetation model; Imaging spectrometer; Biodiversity; Net primary production; River floodplain; PRI

1. Introduction

River floodplains are biodiversity hotspots in northwestern Europe (Ward et al., 2002). However many of the floodplains have been converted to intensive agricultural use during the last century, which led to a decline in biodiversity. In the Netherlands, the gradual termination of agricultural use of these floodplains, as well as the decreasing pollution of river water, has led to an increase of biodiversity (Nienhuis et al., 2002). Recent flooding events in the Netherlands and elsewhere have drawn attention towards imminent effects of climate change and the need to maintain or even increase river discharge capacity (Kabat et al., 2005). Therefore river management strategies are being developed which aim at both flood protection and nature conservation (Geilen et al., 2004). This results in an important challenge as river

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floodplain systems are complex ecosystems. The lack of detailed information about functional relationships and processes at the landscape and catchment scale currently hampers assessment of their ecological status (Jungwirth et al., 2002).

Spatiotemporal modeling approaches are increasingly being used to assist river managers in the evaluation of the effectiveness of measures to reduce flooding risks and to prevent loss of biodiversity (Baptist et al., 2004; Geilen et al., 2004; Kooistra et al., 2005a). Dynamic vegetation models (DVM) provide cause–effect relationships to predict vegetation development under the influence of different management schemes (e.g., mowing and grazing for grasslands, and thinning in forests) (Wamelink et al., 2003; Wamelink, 2007). Recent advances in biogeochemistry based process models prove that in combination with regional scale remote sensing derived products, promising approaches testing ecological hypotheses as well as assessing and forecasting the state of future landscapes can be achieved (Turner et al., 2004). Several studies have shown how remote sensing derived leaf area index (Hazarika et al., 2005; Zhang et al., 2007), biomass (Kimball et al., 2000; Schaepman et al., 2007) or canopy nitrogen (Ollinger and Smith, 2005) are adopted to constrain an ecosystem model. Such approaches require spatially continuous input of the state of the ecosystem at simulation start and may profit from the assimilation of relevant remote sensing derived biophysical and biochemical state variables of the ecosystem under consideration. In particular imaging spectroscopy based methods allow more detailed and accurate retrieval of vegetation properties (e.g., biochemistry and structure) than is possible with broad-band sensors (Ollinger and Smith, 2005), and they may be applied for the retrieval of relevant vegetation variables with unprecedented accuracy (Schaepman et al., 2004). In recent years, a growing number of studies have applied imaging spectroscopy to assess biodiversity of either the terrestrial (Costa et al., 2007; Geerling et al., 2007; Schmid et al., 2005) or the aquatic part (Hauer and Lorang, 2004) of the floodplain ecosystem. However, the number of studies dealing with a combined remote sensing and dynamic vegetation model approach for floodplain ecosystems is limited (Schaepman et al., 2007).

The objective of this paper is to combine a dynamic vegetation model with regional scale remote sensing derived products to improve the simulation and evaluation of management strategies on the current and future biodiversity status of a floodplain ecosystem. We investigate the effect of floodplain management activities on the development of aboveground net primary production (NPP) and floristic diversity by linking the model chain SMART2-SUMO2-NTM3 (Van Dobben et al., 2002; Kros et al., 2002; Wamelink et al., 2003; Wamelink, 2007) using imaging spectroscopy derived variables for a river floodplain in the Netherlands. The dynamic vegetation model was initialized and validated using remotely sensed data. A scenario analysis using the model chain SMART2-SUMO2-NTM3 was carried out comparing the effect of management activities like grazing and harvest of woody biomass on the potential floristic diversity of the floodplain. Implications for floodplain management and the requirements for further development of the presented approach are discussed.

2. Materials and methods

2.1. Study site and field measurements

The effect of floodplain management activities on biodiversity was evaluated for the Millingerwaard floodplain. The floodplain (51°84'N, 5°99' E) is located along the river Waal, one of the main branches of the river Rhine in the Netherlands (Fig. 1). The floodplain covers an area of about 700 ha and is part of the Gelderse Poort nature reserve with a total area of 6700 ha. Before the 1990s, main land use within the Millingerwaard floodplain was agriculture consisting of production grassland and cropland (e.g., maize). Starting from 1990, the agricultural production was gradually reduced and a nature rehabilitation program was started. The floodplain was allowed to undergo natural succession and a regime of grazing by cattle and horses in low densities was introduced. The current vegetation of the floodplain consists of mixed patches and ecotones, i.e. transitions between communities with a dominance of grass, herbaceous vegetation, or shrub, and a large softwood forest. In addition, several clay pits are present. Nature management aims to increase biodiversity, under the condition that the discharge capacity of the river should be above the critical safety levels during flooding events.

In the two weeks after the acquisition (28/7/2004) of HyMap imagery for the Millingerwaard, extensive ground sampling was carried out. Separate sampling schemes were employed to characterize the mixed canopy structure of grass, herbaceous and shrub vegetation and the forest canopy structure (Mengesha et al., 2005). Softwood forest in the Millingerwaard is dominated by willow trees (*Salix fragilis* and *Salix alba*). The forest canopy has an open structure with a dense undergrowth (*Urtica dioica*, *Arctium lappa*, *Galium aparine*) and open water bodies due to the low elevation and high ground water levels. The non-forest vegetation is characterized by a heterogeneous patchy structure of different vegetation succession stages. Dominant species are *U. dioica*, *Calamagrostis epigejos*, and *Rubus caesius*.

Twenty-one sampling sites were selected (Fig. 1) based on an existing vegetation map created in 2002 for the Millingerwaard (Van Geloof & de Ronde, 2002), complemented by a field survey to adjust for potential changes (Kooistra et al., 2005b). For every sampling site, a relevé plot of 2 × 2 m was established and the coordinates of the central location of each sampling site were determined by a differential global positioning system (DGPS). A vegetation description was recorded for every relevé following the method of Braun-Blanquet (1951). Abundance per species was visually estimated as percentage soil covered by living biomass in vertical projection, and scored in a nine-point scale. All bryophytes, lichens and vascular species that were not readily recognizable in the field were collected for later identification. *Taraxacum* species were taken together as *T. vulgare*, and *Rubus* species were taken together as *R. fruticosus*, except *R. caesius*. No subspecific taxa were used. The vegetation type for every sampling site was classified according to the syntaxonomic nomenclature as described by Schaminée et al. (1998). In addition, a description was made of the soil type, groundwater conditions and management (e.g., grazing) of each sampling site.

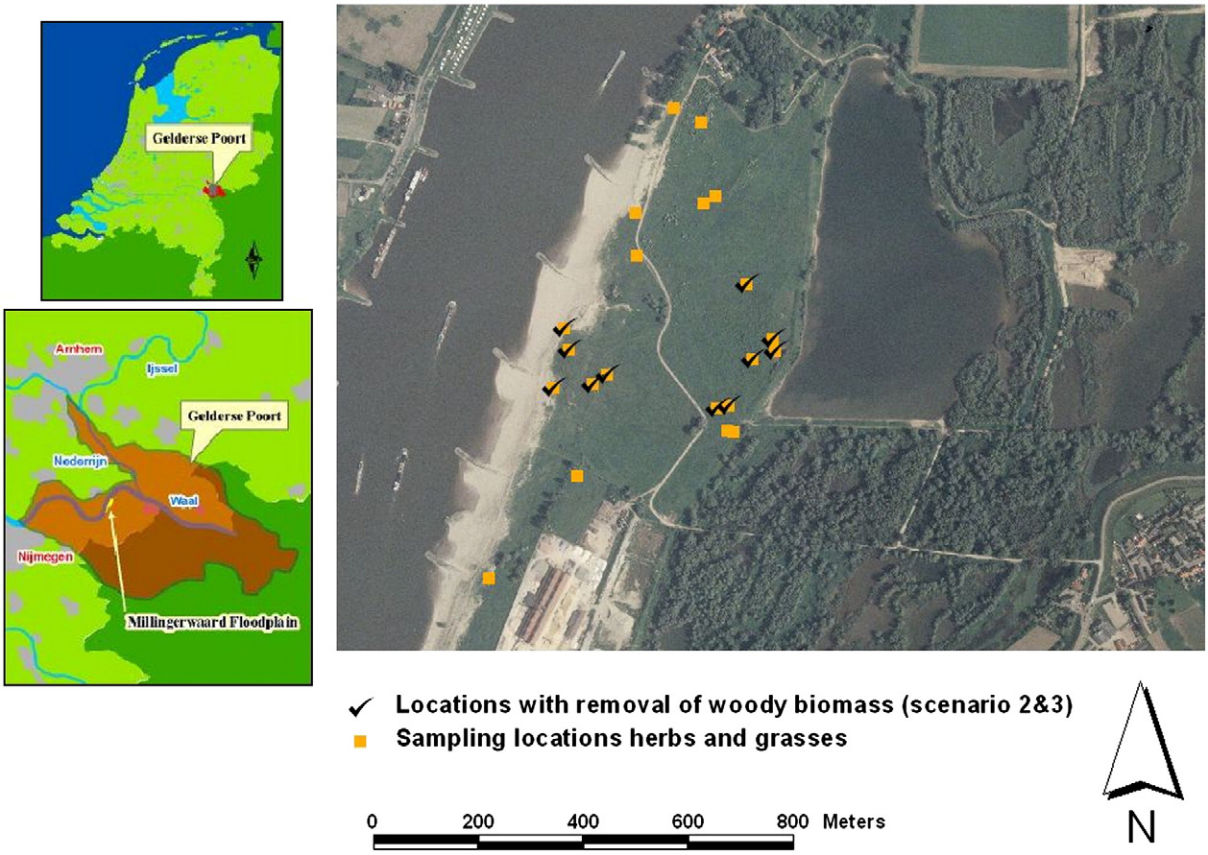

Fig. 1. Location of the sampling sites in the floodplain Millingerwaard. The inset shows the location of the floodplain along the river Waal, the main branch of the river Rhine in the Netherlands.

Vegetation biomass was sampled at the 21 sampling sites using three subplots (0.5 × 0.5 m) with a homogeneous vegetation cover located at three corners of each main plot for which the vegetation description was made. Biomass was clipped at 0.5 cm above the ground level and stored in paper bags. The collected material was air-dried, first for 5 days at room temperature in open bags, and subsequently for 24 h at 70 °C, and weighed. Biomass values for the subplots were averaged to a mean value for the sampling site.

Earlier studies (Knapp et al., 2002; Symstad et al., 2003) indicate that apparent relations can be found between plant species diversity and primary production. Therefore, the assessment of vegetation development in the Millingerwaard floodplain was based on both NPP and the potential floristic diversity derived from SMART2-SUMO2 and the NTM3 model, respectively. NPP, the net amount of carbon fixed in vegetation biomass, is related to plant photosynthetic activity and can be estimated from remotely sensed imagery by observing patterns of light absorption (Sellers, 1995). In this paper, we refer to NPP as the aboveground part of the vegetation which is determined using remotely sensed based methods. An overview of the developed approach for combining regional scale remote sensing with a dynamic vegetation model to assess the biodiversity of the Millingerwaard floodplain is presented in Fig. 2. In the next sections, the different components of the approach are explained in more detail.

2.2. Image data processing

Imaging spectrometer data for the Millingerwaard were acquired on 28th of July 2004 with the airborne HyMap sensor (Integrated Spectronics, Australia) (Cocks et al., 1998). A contiguous spectral range from 450–2480 nm was recorded with a spectral resolution of 15–20 nm in 128 spectral bands. The preprocessed data contained only 126 bands because the first and last band were deleted due to excessive noise. The flight was performed close to the local solar noon (11:38 h UTC) at a solar zenith angle of 33° and solar azimuth angle of 178°. In addition, the flight line was oriented close to the solar principal plane to minimize directional effects of the across-track scanning instrument. The HyMap images were geo-atmospherically corrected using the parametric geocoding approach PARGE (Schlapfer & Richter, 2002) and the atmospheric correction program ATCOR4 (Richter & Schlapfer, 2002) to obtain geo-located surface reflectance. Pre-processing partially compensated for adjacency effects as well as directional effects induced by the atmosphere. There was no particular treatment of the surface induced anisotropy in this approach; as a result the surface reflectance data approximate a Hemispherical Directional Reflectance Factor (HDRF) following the terminology of Schaepman-Strub et al. (2006). The HyMap HDRF data were mapped to UTM projection (Zone 31 N, geodetic datum WGS84) at an equally spaced ground sampling distance of

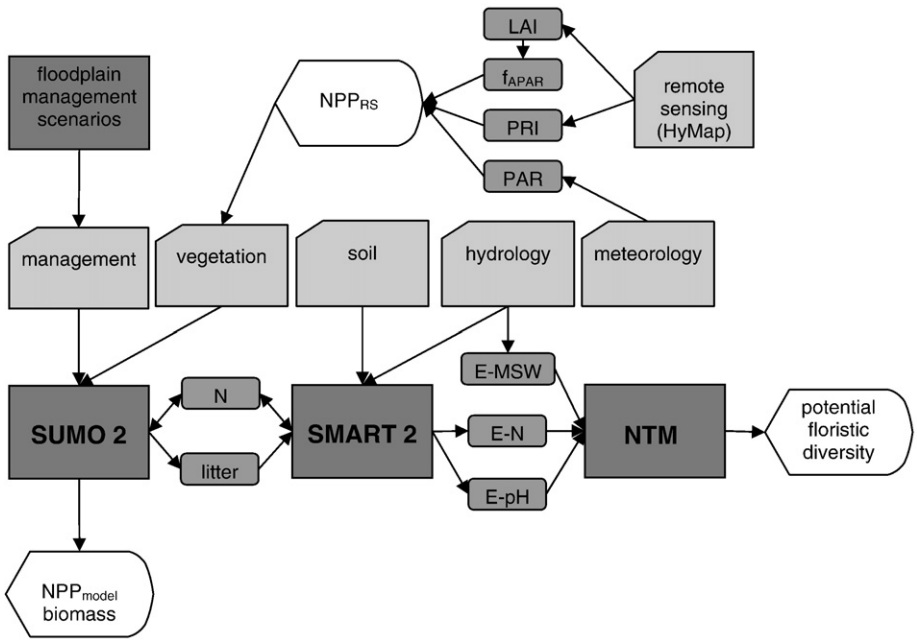

Fig. 2. Schematic overview of the developed approach for combining regional scale remote sensing with a dynamic vegetation model to assess current and future status of river floodplains.

5 m in both axes. An image quality assessment of the pre-processed image was made and the image based signal-to-noise ratio (SNR) per individual band was calculated. This analysis revealed that 9 of the 126 bands (bands at 445 nm, 879 nm, 1403–1418 nm, 1804 nm, 1951–1969 nm, and 2464–2479 nm) should be used with caution, due to limited radiometric performance. Consequently, further analysis was restricted to the remaining 117 spectral bands.

2.3. Derivation of NPP from imaging spectroscopy data

For the estimation of NPP based on imaging spectrometer data in the Millingerwaard, methods for estimating plant productivity from observations of the fraction of absorbed photosynthetically active radiation (f_{APAR}) and light use efficiency as proposed by Monteith (1972, 1977) were adopted. The underlying concept for many remotely sensed measures of carbon uptake is that the ratio of absorbed light to carbon assimilation in most plants is relatively constant (Lobell et al., 2002). This ratio is called the light use efficiency (LUE) and is used to translate remotely sensed estimates of light absorption in NPP following:

$$\mathrm{NPP} = \mathrm{PAR} \times f_{\mathrm{APAR}} \times \mathrm{LUE} \tag{1}$$

where NPP is the aboveground net primary productivity (gC m^{-2} time^{-1}), PAR is total incident photosynthetically active radiation (Wm^{-2}), f_{APAR} is the fraction of PAR absorbed by photosynthetic tissues (unitless), and LUE is the light use efficiency (gC MJ^{-1}).

Regional and global scale NPP studies require accurate estimates of f_{APAR} and LUE (Bradford et al., 2005). LUE is known to exhibit spatial variation over vegetation types (Turner et al., 2002) and temporal variation at individual sites (Ahl et al., 2004). A number of studies (Sims et al., 2006) compared the photochemical reflectance index (PRI) and LUE for structurally complex vegetation, and found significant relations (Rahman et al., 2001; Strachan et al., 2002). The PRI is especially sensitive to changes in xanthophyll pigment activity and thus to light use efficiency (Gamon et al., 1992; Gamon et al., 1997; Penuelas et al., 1995). In this study, LUE was obtained from the PRI which was calculated according to:

$$\mathrm{PRI} = (\rho_{531} - \rho_{570})/(\rho_{531} + \rho_{570}) \tag{2}$$

where ρ_{531} and ρ_{570} indicate reflectance at 531 nm and 570 nm, respectively. The HyMap band 8 (543 nm) and band 10 (573 nm) were used to approximate the required PRI narrow band settings. In this context, we use PRI in its normalized fashion, theoretically ranging between −1 and +1 as described by Rahman et al. (2004). The scaled PRI was calculated by adding 1 to each PRI value and dividing the result by 2. This scaled value of PRI was then used as an approximation for the spatial variation in LUE (Rahman et al., 2004).

The fraction of PAR absorbed by photosynthetic tissues (f_{APAR}) was expressed as function of leaf area index (LAI) (Turner et al., 2002) by an exponential function based on Beer's law (Baret & Guyot, 1991):

$$f_{\mathrm{APAR}} = b_0 \cdot \left(1 - b_1 \cdot e^{(\mathrm{LAI} \cdot b_2)}\right) \tag{3}$$

where b_0 is the asymptotically limiting value of PAR absorption for an infinite limiting thick canopy, b_1 is a coefficient depending on experimental errors and deviation from model

assumption, and b_2 is a coefficient which controls the slope of the relationship (equivalent to an extinction coefficient) (Turner et al., 2002). The value for b_1 was set to 1. Values for b_0 and b_2 were determined from field measurements using the hemispherical camera and were set to 0.9 and 0.38, respectively (Mengesha et al., 2005).

Estimates of LAI for the Millingerwaard floodplain were retrieved using the method proposed by Chen et al. (2002). The Reduced Simple Ratio (RSR) was derived from the HyMap data according to:

$$\mathrm{RSR} = \frac{\rho_{\mathrm{NIR}}}{\rho_{\mathrm{red}}}\left(1 - \frac{\rho_{\mathrm{SWIR}} - \rho_{\mathrm{SWIRmin}}}{\rho_{\mathrm{SWIRmax}} - \rho_{\mathrm{SWIRmin}}}\right) \quad (4)$$

where ρ_{NIR}, ρ_{RED} and ρ_{SWIR} are the reflectance in HyMap band 28 (846 nm), band 15 (650 nm) and band 82 (1661 nm), respectively. ρ_{SWIRmin} and ρ_{SWIRmax} are the minimum and maximum SWIR reflectance in the HyMap image defined as the 1% minimum and maximum cut-off values of the SWIR band histogram. LAI was retrieved and validated using RSR for the softwood forest area (Mengesha et al., 2005) using the transition formula for deciduous forest according to Chen et al. (2002):

$$\mathrm{LAI} = -3.86 \ln\left(1 - (\mathrm{RSR}/9.5)\right) \quad (5)$$

For this study, we applied this relation to the complete floodplain area, independent of land cover type. The derived LAI values were used to estimate f_{APAR} for the Millingerwaard floodplain according to Eq. (3). PAR measurements as recorded at a nearby meteorological station were used for the NPP calculations, with a value of 2.05 MJ m^{-2} at the time of the HyMap acquisition, representing maximum cloud corrected solar irradiance.

Imaging spectrometer derived NPP estimates were converted from mass units of carbon (C) to units of biomass for comparison with SMART2-SUMO2 estimates using 0.475 as the proportion C in vegetation biomass (Raich et al., 1991). The daily estimate of NPP based on the HyMap acquisition was extrapolated to the 1 year temporal resolution of SMART2-SUMO2 assuming a growing season of 180 days.

2.4. Dynamic vegetation modeling

The SMART2 model (Kros et al., 2002) simulates soil processes, SUMO2 (Berendse, 1994; Van Dobben et al., 2002; Wamelink, 2007) simulates vegetation processes and succession, whereas NTM3 (Wamelink et al., 2003) predicts the potential floristic diversity based on groundwater level, nitrogen availability and soil pH. SMART2 and SUMO2 are dynamic process models that include complete nitrogen and carbon cycles, based on time steps of one year. NTM3 is a static model for which the input is mainly being provided by SMART2-SUMO2. Below the three models are described in more detail.

The model SMART2 (Kros et al., 2002) describes linked biotic and abiotic processes in the soil solution as well as in the solid phase. The model considers the inorganic soil and two organic soil compartments. The chemistry of the soil solution depends on the net element input from the atmosphere and ground water, canopy interactions, geochemical interactions in the soil and nutrient cycling (including fertilization). SUMO2 provides estimates for nutrient uptake and litterfall (including roots, branches and stemwood). SMART2 delivers the nitrogen availability to SUMO2 as the sum of external N input and mineralization. Due to the time step of one year, inter-annual variation of the groundwater table is not accounted for. The groundwater level is mainly determined by the water level in the river Waal adjacent to the floodplain. The mean annual water level in the river has been stable over the past decades (Van Geest et al., 2005), therefore the groundwater table in the presented model application was assumed to be stable over time.

Vegetation succession and biomass production are modeled by SUMO2 (Berendse 1994; Van Dobben et al., 2002; Wamelink et al., 2005). The biomass production in root, shoot and leaf is simulated for five functional types (FT): (1) herbs and grasses; (2) dwarf shrubs; (3) shrubs; (4) pioneer trees; and (5) climax trees. The five FT compete with each other for nitrogen (including nitrogen deposition), light, and moisture. Competition for nitrogen is based on the amount of biomass present in the roots of each FT. Competition of light is a function of the height and the leaf biomass of the FT. Actual biomass growth of each FT is the result of a reduction of maximum growth by moisture, nitrogen and light availability. Management (e.g., mowing and grazing in grassland, thinning in forest) is described as removal of part of the biomass (including carbon and nitrogen) from the system. Net primary production (NPP) is divided over root, shoot and leaf and calculated by SUMO2 as biomass difference between consecutive years taking into account litterfall and biomass removal through management (e.g., grazing). SUMO2 requires information on soil type and groundwater level, the initial vegetation type and nature management. The model is initialized with a standard amount of biomass for each functional type. This initial biomass may be derived from a general model run or, as in this paper, from remote sensing derived biomass estimates. SMART2 and SUMO2 share information on litter fall and nitrogen availability on a yearly basis, i.e. soil parameters are influenced by biomass parameters and vise versa on a yearly basis.

NTM3 (Wamelink et al., 2003) is a regression model that predicts the potential floristic diversity at given values of the soil characteristics nitrogen availability, soil pH and moisture availability for four different ecosystems (grassland, heathland, deciduous forest and coniferous forest). The nitrogen availability and soil pH are simulated by SMART2. The moisture availability is derived from a hydrological map. A nature conservation value (NCV) was assigned to the vascular plant species occurring in the Netherlands, based on the Red List criteria, i.e. the rarity, the temporal trend and the size of the distribution of each species (Mace and Stuart, 1994). Based on this approach, rare and decreasing species that have their major distribution in the Netherlands (i.e. The Netherlands contains a major part of the population of the species) have a high NCV, common species get a low value or even a negative value when they are increasing (e.g., invasive species). A dataset containing 160,000 vegetation

descriptions (Hennekens & Schaminée, 2001) was used as a training set to relate NCV to vegetation structure and soil properties (soil acidity, nutrient availability and groundwater table; cf. Wamelink et al., 2003). The calculated NCV for the vegetation descriptions is regressed on the three soil variables using non-linear regression techniques (p-splines). Separate regression models for four ecosystem types have been developed: grassland, heathland, deciduous forest and coniferous forest (Wamelink et al., 2003). The output of NTM3 is referred to as the potential floristic diversity and is expressed in an ordinal scale ranging between 7 and 19. Values larger then 13 indicate a high probability of occurrence of Red List species (Tamis et al., 2004), and values smaller then 9 indicate a low floristic diversity with a very low probability of occurrence of red list species. The model estimates the probability of occurrence for red list species under the assumption that sufficient recolonization can take place if conditions improve. For this reason the output of NTM3 is described as potential floristic diversity.

2.5. Linking imaging spectroscopy and dynamic vegetation models

The model chain SMART2-SUMO2-NTM3 is point based, and thus does not describe spatial (horizontal) interaction. As a result the models can be applied on various spatial scales. In order to run the model chain on a regional or national scale, spatially explicit data are required. A common problem in dynamic vegetation modeling is the limited availability of spatially explicit data for model initialization. This lack of initialization data requires the model to compute initial levels of biomass within a functional type, which can result in high uncertainties for these initial values. In this study we use imaging spectrometer derived NPP to provide the required initialization data for the SMART2-SUMO2 model.

The model chain SMART2-SUMO2-NTM3 was run for the 21 grassland and herbaceous vegetation sites in the Millingerwaard. The model chain was run over a period of 81 years from 1970 to 2050. The first 25 years are used for initialization. The initialization of SMART2-SUMO2 in 1970 assumed standard biomass values for countrywide applications of both agricultural and natural grassland. Hydrology was assumed to be constant over time. Soil type and stocking density for grazing were estimated from field observations per sampling plot. The output of the model chain consists of the potential plant diversity per vegetation type in 2050 and the temporal development of NPP for the 21 sampling plots in the Millingerwaard.

A scenario-based approach was adopted to investigate the influence of floodplain management on the future development of potential plant diversity in the Millingerwaard. Scenarios are based on a newly developed floodplain management strategy in the Netherlands (Baptist et al., 2004; Duel et al., 2001). This strategy, cyclic floodplain rejuvenation (CFR), aims at safeguarding flood protection and biodiversity conservation through anthropogenic rejuvenation of floodplain ecosystems (e.g., removal of softwood forest, lowering of floodplains and construction of secondary channels). For this study, three scenarios were compared, and implemented in SMART2-SUMO2-NTM3:

Scenario 1 (‘extensive grazing’): extensive management aiming at nature rehabilitation and increase of biodiversity with limited grazing (1 grazing unit per hectare) and a non-restricted development of all functional types. This has been the management until the present day after the Millingerwaard was taken out of agricultural use;

Scenario 2 (‘woody biomass removal’): intensive management aiming at flood protection according to the strategy of CFR. For all 21 sampling plots, woody biomass (shrub and softwood forest) is completely removed in a 5 year cycle starting in 1995 at the start of nature rehabilitation project in the Millingerwaard. Woody biomass is removed because of its large effect on hydraulic resistance during flooding (Baptist et al., 2004).;

Scenario 3 (‘partly woody biomass removal’): management aiming at the combined objective of flood protection and nature rehabilitation through site-specific removal of all woody biomass for a selected part of the floodplain in a 5 year cycle starting in 1995. Removal of woody biomass is carried out in a corridor area which enables increased discharge during high floods. The sampling plots, for which woody biomass was removed in this scenario, are indicated in Fig. 1, woody biomass is removed in 11 of the 21 plots.

Model validation was performed by comparing imaging spectrometer derived NPP values for the 21 sampling plots with the SMART2-SUMO2 simulated NPP in 2004. In a next step, the SMART2-SUMO2 model was re-initialized with imaging spectrometer derived NPP values using a forcing approach (Dorigo et al., 2007; Barrett et al., 2005). This means that the model estimated values of NPP in 2004 were replaced by the remote sensing derived NPP values. In addition, the percentage coverage of the different functional types was updated based on the vegetation descriptions which were made in the field for the 21 sampling plots.

Forecasts until 2050 were made of NPP derived from SMART2-SUMO2 and potential floristic diversity derived from NTM3 for all three management scenarios. This means that for every scenario the model chain SMART2-SUMO2-NTM3 was run with and without initialization using imaging spectroscopy derived variables.

3. Results and discussion

3.1. Imaging spectroscopy derived variables

Values for PRI range between 0 and 0.6 and varied considerably over the study area (Fig. 3). Relatively low values (0.1–0.3) are found in the scarcely vegetated areas along the river, in the grass and shrub vegetated area in the centre of the floodplain and in the softwood forest. Low PRI values for the softwood forest are the result of the mixed influence of small lakes and of shadowed pixels in this area. High values for PRI (0.5–0.6) are found in agricultural fields and in herbaceous patches in the Millingerwaard dominated by *U. dioica*. Comparison of PRI values with LUE values reported in literature (Gower et al., 1999; Ahl et al., 2004) shows reasonable

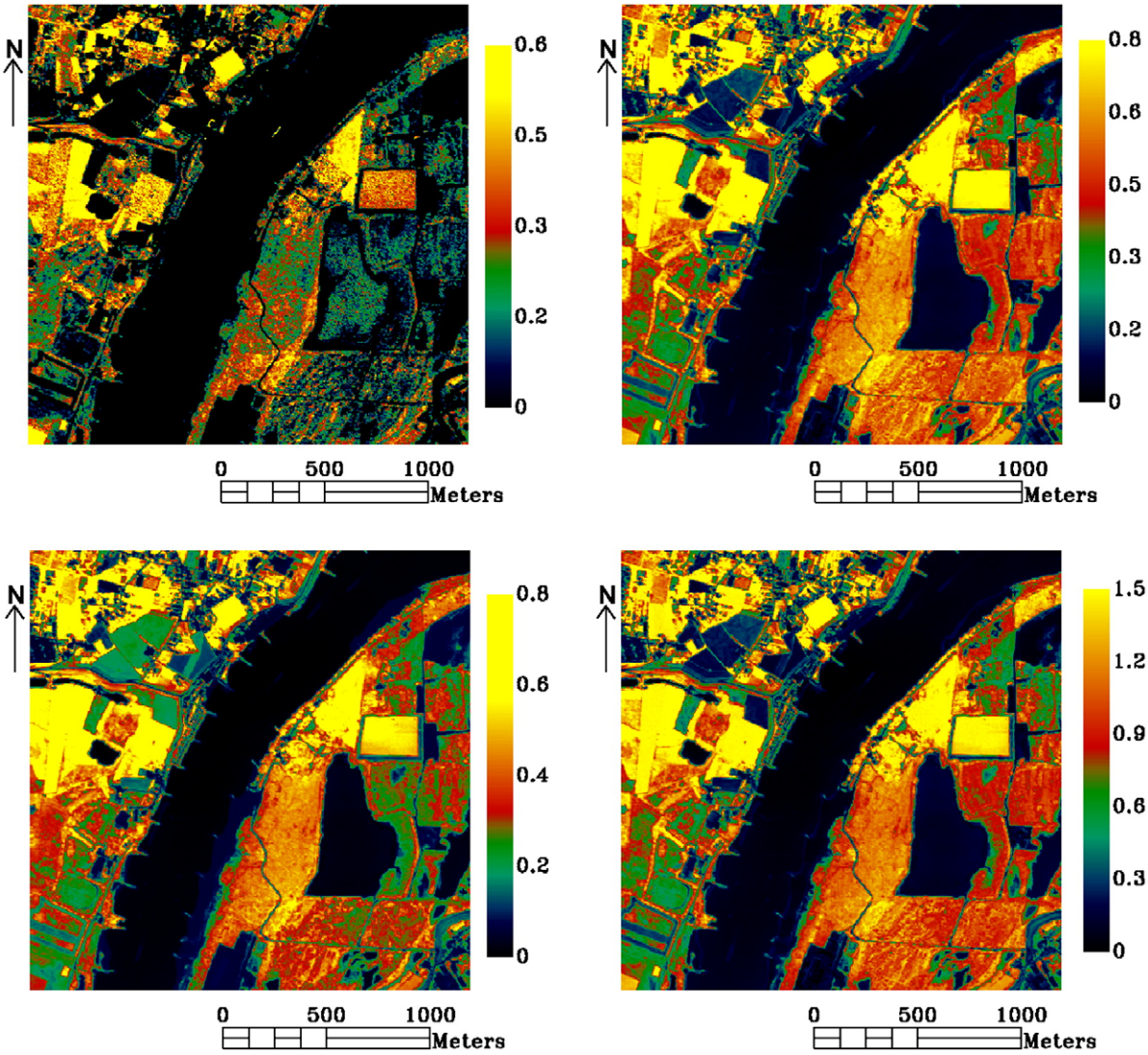

Fig. 3. Imaging spectroscopy derived spatial distributed Photochemical Reflectance Index (upper left), Leaf Area Index (upper right), fraction of absorbed photosynthetically active radiation (lower left), and Net Primary Production (lower right) for the Millingerwaard floodplain along the river Waal.

agreement for mixed grass and shrub vegetation (0.3) and forested wetland (0.41). PRI values for cropland are underestimated compared to literature reported LUE values determined from field studies (2–4) (Ahl et al., 2004; Lobell et al., 2002). Earlier studies identified large differences between remote sensing derived and field measured values for LUE (Lobell et al., 2002; Ruimy et al., 1994). For this study, the difference is partly explained by the applied normalization procedure (Rahman et al., 2004) for scaling PRI values between 0 and 1. In addition, recent studies (Sims et al., 2006) indicate that for local environmental conditions empirical relations can be derived between PRI and LUE, but the mechanistic basis for the generalization of these relationships across vegetation types is currently under investigation since several physiological and structural factors may affect PRI (Verrelst et al., 2007, in press).

Imaging spectroscopy derived LAI values for the Millingerwaard (Fig. 3) ranged between 1.5 and 4.5 for the grass and shrub vegetated area and between 4.5 and 6 for the agricultural fields. The relatively lower LAI values (1.5–3.5) for the soft-wood forest can be related to the clumped nature of the forest canopies (Mengesha et al., 2005). Based on the Beer's law approach (Eq. (3)), imaging spectroscopy derived LAI was used to derive f_{APAR} for the study area (Fig. 3). Again, resulting f_{APAR} values were high for agricultural areas (0.6–0.8) compared to natural vegetated areas (0.3–0.5).

Site-specific NPP was mapped for the Millingerwaard floodplain (Fig. 3) using Eq. (1) and taking into account the remote sensing derived values for PRI and f_{APAR}. The spatial distribution of NPP shows a clear dependence with land cover. Low NPP values (0–0.6 MJ m^{-2} day^{-1}) were associated with bare soils and low vegetated areas. Moderate NPP values (0.61–1.1 MJ m^{-2} day^{-1}) were mainly found for natural vegetated areas. For the grass and shrub area, the spatial variability is low, while the forested area exhibits small scale NPP variations due to the heterogeneity of the canopy cover. High NPP values (1.11–1.5 MJ m^{-2} day^{-1}) were associated with agricultural fields and some highly productive species (e.g., *U. dioca*) in the naturally vegetated areas.

3.2. Validation of SMART2-SUMO2-NTM3 results

A comparison of SMART2-SUMO2 modeled estimates for biomass and NPP was made with field measured biomass and imaging spectroscopy derived estimates for NPP, respectively. For this comparison the SMART2-SUMO2 estimated values of biomass and NPP for scenario 1 in 2004 were used with initialization of the model starting in 1970. The biomass derived from destructive sampling for 21 sampling plots was in good agreement (R^2=0.60) with SMART2-SUMO2 modeled biomass for these plots (Fig. 4). Some lower field biomass values (2–4 ton/ha) are underestimated by the model; however, the values at the higher end of the distribution are estimated with a reasonable accuracy. In this context, comparison of field and modeled biomass can be considered as validation of the SMART2-SUMO2 model. The output of the model is defined as the maximum biomass at the peak of the growing season. For grass and shrub vegetation types this peak is in the beginning of August which coincides with vegetation biomass sampling period in this study.

Total annual NPP simulated by the SMART2-SUMO2 model compared relatively well (R^2=0.46) with imaging spectroscopy derived NPP values (Fig. 5). Model estimates for NPP in 2004, taking into account management activities as described for scenario 1, were made for the 21 sampling locations. Some sampling sites are subject to a high grazing intensity due to preferential grazing behavior. This effect is reflected in relatively low values for both model and remote sensing derived NPP. Remote sensing derived NPP values at the higher end of the range show a negative bias compared to model derived NPP. This can be attributed to the development of the woody part of biomass which is not accounted for in the HyMap estimate. Although vegetation for the 21 plots is dominated by grass and herbaceous species, some species with a high productivity (e.g., *R. caesius*, *U. dioica*) have a large woody fraction.

In general, a satisfactory agreement is found between field observations and model estimates on the one hand, and model estimates and remote sensing derived variables on the other hand. Both model and remote sensing derived aboveground NPP estimates fell within the range of values reported for grassland ecosystems in temperate regions (Table 1). Compared to NPP estimates from the Millingerwaard floodplain, reduced values of NPP are observed for ecosystems in a limiting environment (e.g., temperature Turner et al., 2005 or water availability Wang et al., 2007). In the case of an undisturbed development of grassland vegetation, relatively higher NPP values can be achieved (De Vries et al., 2007; Esser, 1998). Differences between NPP values from Millingerwaard and the other natural grassland location in the Netherlands (De Vries et al., 2007) are mainly explained by the influence of nature management (e.g., grazing) and differences in soil composition. The sandy levee soils along the river have a relatively low production compared to the grassland vegetation on clay soils (De Vries et al., 2007). The relatively higher NPP value reported for a forest floodplain (Clawson et al., 2001) indicates that an increasing abundance of woody functional types (shrubs and forest) could result in an increased NPP.

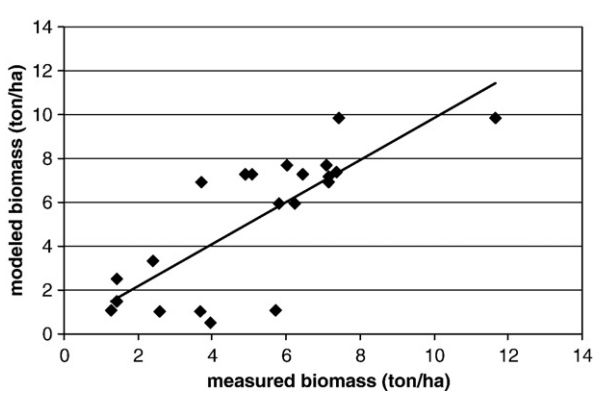

Fig. 4. Comparison of field measured biomass with SMART2-SUMO2 modeled biomass for 21 sampling plots in the Millingerwaard (R^2=0.60). Modeled biomass values are taken from the SMART2-SUMO2 run in 2004 for scenario 1 ('extensive grazing').

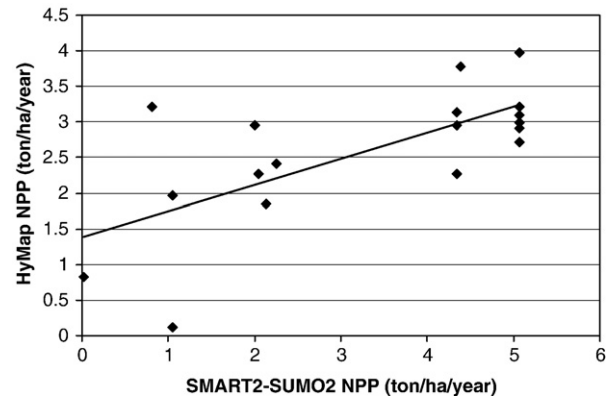

Fig. 5. Comparison of imaging spectrometer derived NPP and SMART2-SUMO2 modeled NPP for 21 sampling plots in the Millingerwaard (R^2=0.46). Modeled NPP values are taken from the SMART2-SUMO2 run in 2004 for scenario 1 ('extensive grazing').

3.3. Scenario analysis

3.3.1. Development of NPP

Comparison of three floodplain management scenarios shows a comparable development of simulated annual NPP for all functional types in the Millingerwaard (Fig. 6). The removal of woody biomass in a 5 year cycle for scenario 2 and 3 can be observed as a small reduction in NPP in 1995 compared to scenario 1. Oscillations in NPP development in the first years after (re-)initialization are due to model instability (Fig. 6). Main differences are caused by re-initialization of the original scenarios with imaging spectroscopy derived NPP values in 2004. NPP increases from approximately 4.8 ton ha^{-1} y^{-1} in 1970 to 6 and 7 ton ha^{-1} y^{-1} in 2050 for the scenarios with and without re-initialization, respectively (Fig. 6). This difference can partly be attributed to the lower imaging spectrometer derived NPP values which were used for re-initialization of the model in 2004 (Fig. 5). In addition, the composition of

Table 1
Comparison of aboveground NPP estimates for grassland ecosystems in temperate regions

Vegetation type	Type of measurement	NPP (ton ha^{-1} $year^{-1}$)	Temperature (°C)	Country	Source
Grassland	RS derived	2.66	9.8	Netherlands	Present study
Grassland	Simulated	3.47	9.8	Netherlands	Present study
Grassland — tundra	RS derived	0.64	−10.9	USA	Turner et al., 2005
Grassland — desert	RS derived	0.54	13.5	USA	Turner et al., 2005
Grassland — prairie	Field	6.02	7.2	USA	Esser, 1998
Grassland	Field	7.2	7.3	Sweden	Esser, 1998
Grassland	Field	6.15	9.8	Netherlands	De Vries et al., 2007
Grassland	Field	2.03	4.9	China	Wang et al., 2007
Grassland	Field	1.31	4.9	China	Wang et al., 2007
Forest — floodplain	Field	5.83	13.4	USA	Clawson et al., 2001

functional types has been re-initialized according to field observations resulting in a reduced tree biomass.

The effect of floodplain management activities on NPP development is most pronounced for the woody functional types, i.e., shrub and forest (Fig. 7). Removal of the woody part of the vegetation in 1995 and periodic forest removal results in a significant decrease of NPP for scenarios 2 and 3. This effect is most pronounced for scenario 2 for which trees are removed periodically in all 21 plots. Re-initialization of the model in 2004 with remote sensing derived NPP resulted in an additional decrease of NPP for the functional types shrubs and trees. This can mainly be attributed to reduced contribution of the tree functional type which was re-initialized according to field observations for the situation in 2004.

In the central part of the floodplain, current vegetation succession shows a gradual increase of shrub coverage (e.g., *Craetegus monogyna*) at the expense of grass and herbaceous vegetation types. This increase is reflected in vegetation biomass development for scenario 1 that shows an increasing contribution of the shrub and tree functional types. Although total biomass for scenarios 2 and 3 decreases compared to scenario 1 (Fig. 8), annual biomass production, i.e., NPP, is at a comparable level (Fig. 6). This can partly be explained by the contribution of herbaceous species like *U. dioica* which have a high annual productivity. However, at the end of the growing season biomass is returned as litter to the soil, and total vegetation biomass of the system is not increasing. For scenario 1, increasing biomass values are the result of storage in the woody parts of the vegetation, while for scenario 2 and 3 this woody part is periodically removed. Re-initialization of the SMART2-SUMO2 model in 2004 shows not only the contribution of imaging spectroscopy derived NPP to final model results in 2050 (Fig. 6), but also the influence of the composition of functional types of the sampling plots in 2004 which is an important driver for the 2050 NPP estimate. For this study, we derived the composition of functional types from field observations. Further research will focus on the development of a remote sensing based approach for deriving plant functional types (PFT) which can be adopted to characterize the abundance of specific functional types as required by dynamic vegetation models like SMART2-SUMO2 (Bonan et al., 2002).

3.3.2. Potential floristic diversity

The SMART2-SUMO2-NTM3 derived potential floristic diversity in 2050 for the three defined river management

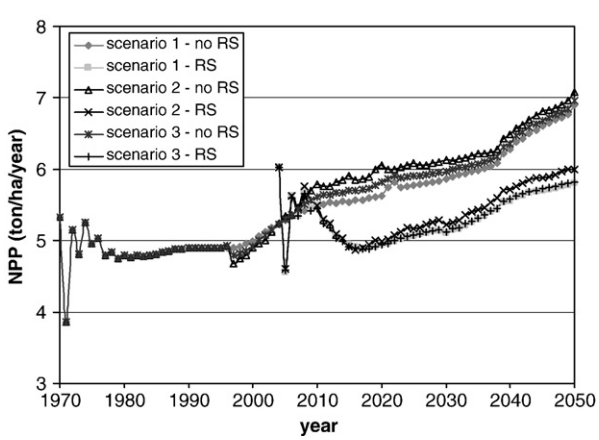

Fig. 6. Development of total Net Primary Production (ton/ha) for all functional types in the Millingerwaard until 2050 simulated using SMART2-SUMO2 for three floodplain management scenarios: scenario 1 ('extensive grazing'); scenario 2 ('complete woody biomass removal'); and scenario 3 ('partly woody biomass removal'). Each scenario is run with a standard initialization in 1970 ('no RS'); and with initialization in 2004 using imaging spectrometer derived estimates for NPP ('RS').

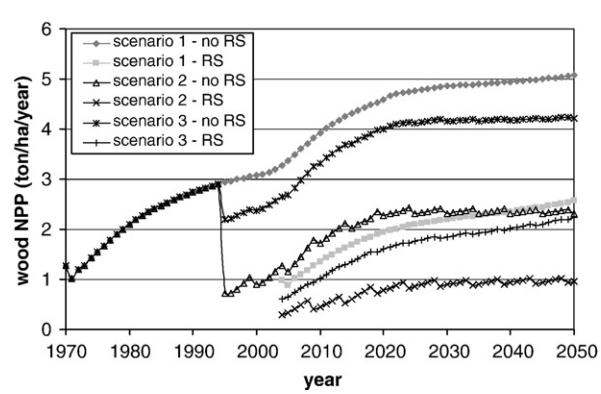

Fig. 7. Development of total Net Primary Production (ton/ha/year) for the functional types shrubs and trees in the Millingerwaard until 2050 simulated by SMART2-SUMO2 for three floodplain management scenarios: scenario 1 ('extensive grazing'); scenario 2 ('complete woody biomass removal'); and scenario 3 ('partly woody biomass removal'). Each scenario is run a standard initialization in 1970 ('no RS'); and with initialization in 2004 using imaging spectrometer derived estimates for NPP ('RS').

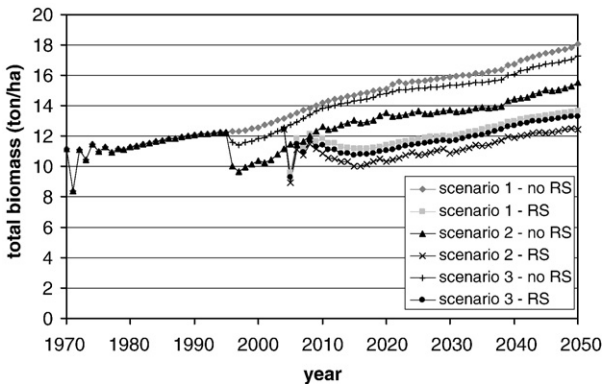

Fig. 8. Development of total biomass (ton/ha) for all functional types in the Millingerwaard until 2050 simulated using SMART2-SUMO2 for three floodplain management scenarios: scenario 1 ('extensive grazing'); scenario 2 ('complete woody biomass removal'); and scenario 3 ('partly woody biomass removal'). Each scenario is run with a standard initialization in 1970 ('no RS'); and with initialization in 2004 using imaging spectrometer derived estimates for NPP ('RS').

scenarios in the Millingerwaard floodplain were compared to diversity values in 2004 (Fig. 9). All the scenarios show a clear increase of the potential floristic diversity in 2050. Compared to studies at the national scale (Wamelink et al., 2003), the floodplain represents an area with a high floristic diversity potential (>13), which agrees with the general idea that floodplain ecosystems are valuable.

Differences between the scenarios are relatively small for the mean floristic diversity of grassland ecosystems (Fig. 9). The standard error in Fig. 9 represents the spatial variability between the sampling sites. Initialization using spectrometer derived NPP ('RS') results in an increased spatial heterogeneity of floristic diversity as represented by high values for the standard error. Especially, scenario 2 (periodical removal of all trees) shows a high spatial variability which can be attributed to an increased contribution of rare pioneer species for some of the harvested plots. Due to tree removal in 2050, no floristic diversity value for the forest ecosystem plots can be calculated for scenario 2.

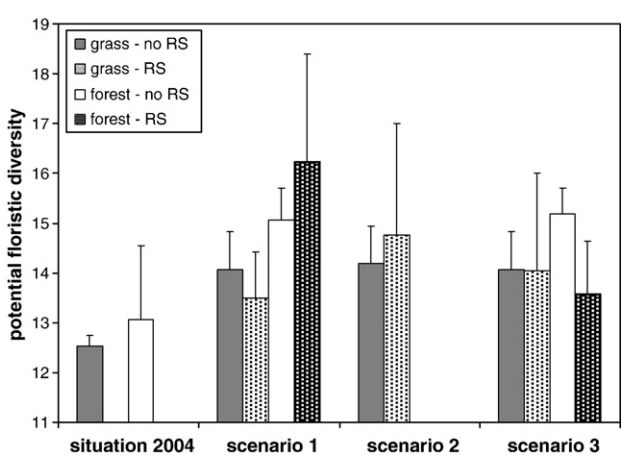

Fig. 9. Comparison of NTM3 estimated potential floristic diversity in 2004 and three scenarios in 2050 for the floodplain Millingerwaard. A differentiation is made for diversity in grassland and forest ecosystems. The three floodplain management scenarios are: scenario 1 ('extensive grazing'); scenario 2 ('complete woody biomass removal'); and scenario 3 ('partly woody biomass removal'). Each scenario is run with a standard initialization in 1970 ('no RS'); and with initialization in 2004 using imaging spectrometer derived estimates for NPP ('RS').

The results of scenario 1 show that forest development has a clear effect on floristic diversity (Fig. 9). Due to succession, a more diverse ecosystem will be present in 2050 which gives a relative high diversity value. Moreover, since not all plots will consist of a forest ecosystem, the diversity will be much higher compared to the scenario where all trees are removed and only grassland will be present, i.e. the spatial diversity will be higher when forestation is allowed in certain areas of the floodplain. This variability is larger for the model runs started in 2004, which are initialized using RS data. Clear differences are observed in forest development between scenario 1 and scenario 3, where extensive grazing gives a higher diversity than the untreated sites in the partly tree removal scenario. This indicates that the influence of grazing on the quality of the forest that evolves may be quite large. Compared to the model runs that started in 1970, it looks like that eventually the differences may disappear and the diversity in forest ecosystems may initially increase, but later on decrease again. Links between diversity and biomass are well known (Grime, 1979; Schaffers, 2002; Marriott et al., 2004). In general, higher biomass results in lower floristic diversity. These results indicate that especially the intermediate succession stages of shrubs and pioneer trees are important contributors to floristic diversity in river floodplains.

For reference, future potential floristic diversity (Fig. 9) was compared with the historic development of actual diversity in the floodplain (Table 2). Actual floristic diversity was based on the nature conservation value (Mace and Stuart, 1994) calculated from available vegetation relevés in the years 1954, 1967, 1975 and 2004. For all relevés, presence and abundance of species were sampled according to the method of Braun-Blanquet (1951). In the 1950s, the floodplain is considered a valuable area with a large variation in the field as represented by the high value for the standard error. During the 1960, agricultural activities resulted in a clear decrease of plant diversity, while also the spatial variability was minimized. Starting from the middle of the 1970s an improvement of the actual plant diversity can be observed. Recent

Table 2
Historical development of the actual floristic diversity for the floodplain Millingerwaard

Year	*n*	Nature conservation value			
		Grass		Forest	
		Mean	S.E.	Mean	S.E.
1954	3	12.6	1.9	n/a	n/a
1967	10	7.2	0.3	n/a	n/a
1975	5	10.1	2.4	n/a	n/a
2004	21	9.1	1.07	9.76	1.66

The nature conservation values are derived from available vegetation relevés in the years 1954, 1967, 1975 and 2004. The standard error (S.E.) represents the spatial variability between the sampling sites.
n/a indicates that no vegetation relevés for forest ecosystems were available for these years.

observations in 2004 show the contribution of forest ecosystems to plant diversity. Deviations of actual field derived diversity values (Table 2) from potential modeled values (Fig. 9) indicate that future management practices should aim at the improvement of recolonization conditions of more valuable plant species.

The results of the scenario analysis for the Millingerwaard floodplain indicates that intensive management activities (e.g., forest removal) are mainly affecting total biomass (Fig. 8) and to a lesser extent NPP (Fig. 5). Shifts of floristic diversity can be observed (Fig. 9) when changes are quantified specifically for forest and non-forested ecosystems, however total plant diversity between scenarios is comparable. Floodplain management according to the strategy of cyclic rejuvenation should focus on both. As sampling sites were located in areas with a dominating grass and herbaceous coverage, general conclusions on the effect of floodplain management activities on river landscape biodiversity can only be made when sites with shrub and tree coverage are also accounted for.

Re-initialization of the SMART2-SUMO2-NTM3 model chain with imaging spectroscopy derived variables resulted in lower estimates for total NPP (Fig. 6) and total biomass in 2050 (Fig. 8) compared to model runs without initialization. Re-initialization had a limited effect on total values for floristic diversity except for an increase of the spatial variability (Fig. 9). However, floristic diversity specified for forest and non-forest ecosystems indicated some clear differences between scenarios.

3.4. Linking remote sensing and dynamic vegetation models: limitations and opportunities

Scaling biodiversity from the plot to the landscape scale is one of the central issues in the ecological domain. In this study, we have investigated the linkage of remote sensing and dynamic vegetation models as a solution to bridge these scaling gaps. To assess the uncertainties in the presented approach, an overview of the limitations and assumptions in both the remote sensing methodology and the modeling chain is an important requirement. Main sources of uncertainty for the model chain SMART2-SUMO2-NTM are related to the SMART2-SUMO2 vegetation parameters (e.g., maximum growth rate, initial biomass) which have the largest contribution to the uncertainty in the potential floristic diversity (Schouwenberg et al., 2000). In this case remote sensing derived NPP was used to test the model outcome and subsequently to re-initialize model parameters and evaluate the effect on biodiversity for future floodplain management scenarios.

Annual NPP estimates from both the model and remote sensing for this case study fell within the range of values reported for grassland ecosystems in temperate regions (Table 1). However, additional work is required to improve the remote sensing based estimation of seasonal NPP development. In the current study, the one day estimate for NPP was extrapolated assuming a growing season of 180 days, which is corresponding to the NPP representation in SMART2-SUMO2. A more accurate estimation of NPP would need multiple image acquisitions over the year to characterize the seasonal development of PRI and f_{APAR}. Turner et al. (2004) identified limiting opportunities for validation of NPP products derived from coarse resolution sensors (e.g., MODIS). The approach presented in this study offers the opportunity to validate these products by combining fine-scale remote sensing with dynamic vegetation models which at a later stage can be adopted for up-scaling.

Model inputs on the hydrology of the floodplain as required for the NTM model were represented in a relatively simple way. Groundwater was assumed stable over the years. However, this is justified by the relatively stable level of the river Waal which is the main determent of the groundwater level in the Millingerwaard floodplain. Inter-annual variation of the ground water level could not be taken into account due to the one year modeling time step of the SMART2-SUMO2-NTM model. This is especially important during flooding events when water levels are above the ground level. On one hand, the vegetation in the floodplain is adapted to these flood events (Van Eck et al., 2005), on the other hand the timing of the flood event (e.g., late spring or summer) can have an important influence on the development of vegetation biomass within the season. Although this could mean that during occasional years vegetation development is hampered by flooding events, over the scenario period of almost 50 years, it has a low influence on the estimates for the potential floristic diversity. However, arguably neither the models nor the scenarios are well prepared to currently include and predict increasing inter-annual extreme events. Once a predictive capacity model chain has been implemented, this will be the most important challenge to tackle.

For this study, we substituted the model NPP with the remotely sensed NPP values, resulting in a simple feed-forward forcing. In literature, various methods have been described to integrate remotely sensed observations in agroecosystem models (e.g., Dorigo et al., 2007). Additional work is still required to arrive at an optimal data-assimilation strategy, in this study the adopted type of dynamic vegetation models.

4. Conclusions

The results of this study demonstrate that imaging spectrometer derived products can be used for validation and initialization of a dynamic vegetation model like SMART2-SUMO2. Results for a case study in a floodplain ecosystem show that modeled estimates of NPP and imaging spectrometer derived values were well in agreement ($R^2=0.46$). Also a good agreement was found between field observations for biomass and model estimated values ($R^2=0.60$). Combination of SMART2-SUMO2 with the nature valuation model NTM3 allowed the assessment of potential plant diversity for the investigated floodplain. The use of site-specific imaging spectrometer based estimates of NPP and LAI for initialization of SMART2-SUMO2 increases the reliability for the assessment of current and future biodiversity. Re-initialization of the DVMs using remote sensing derived variables resulted in lower estimates for biomass and NPP, however, plant diversity was comparable with scenarios without re-initialization.

The analysis of the defined floodplain management scenarios indicated clear difference between scenarios in spatial and temporal development of NPP and floristic diversity. Floristic diversity estimates for individual ecosystems indicated increased spatial variability for forest ecosystems compared to the grass ecosystem. This shows that floodplain management

according to the strategy of cyclic rejuvenation should not treat a floodplain area as one general spatial unit, but instead should take advantage of the spatiotemporal dynamics of the floodplain as a basis for increased biodiversity. In addition, future management practices should aim at the improvement of recolonization conditions of more valuable plant species. The derived and predicted biodiversity can be used at scales beyond regional, allowing floodplain managers to implement protective measures at river catchment scale. In combination with climate-risk scenarios, the presented combined remote sensing and vegetation model approach is most useful for a sustainable and risk-balanced planning for river floodplains.

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