

Fuzzy modelling and mapping soil moisture for observed periods and climate scenarios. An alternative for dynamic modelling at the national and regional scale?

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Abstract

• **Key message** Average soil moisture was spatially modelled for observed periods and climate scenarios using a fuzzy logic approach. Accordingly, a significant decline of soil moisture until 2070 in Germany and the Kellerwald National Park could be evidenced for soils influenced by ground water and by stagnant water and at sites on steep slopes and on southerly slopes.

• **Context** Soil moisture is an essential environmental factor affecting the condition of forests throughout time with high spatial variance. To adapt forests to climate change, assessments of ecological integrity and services in forest management and nature conservation need spatio-temporal estimations of current and future soil moisture. Dynamic modelling of soil moisture even with rather simple models needs numer-

ous data which are often not available for areas of large spatial extent.

• **Aims** Therefore, the objectives of this investigation were to (1) spatio-temporally estimate ecological soil moisture with available data covering the whole territory of Germany, (2) to specify these estimates for the regional scale, (3) to statistically analyse temporal trends of modelled soil moisture for the time period 1961–2070 and (4) to map soil moisture changes (drying-out) at both national and regional levels.

• **Methods** A fuzzy rule-based model was developed allowing the combination of a pedological and an ecological soil moisture classification. The fuzzy modelling approach was applied for mapping average soil moisture at two spatial scales.

• **Results** Soil moisture was modelled and mapped on a scale of 1:500,000 across Germany and regionally specified on a scale of 1:25,000 for the Kellerwald National Park for the time intervals 1961–1990, 1991–2010, 2011–2040 and 2041–2070. The model validation gave a root mean squared error (RMSE) of 0.86 and a coefficient of determination (pseudo R^2) of 0.21. Average soil moisture was expected to decline significantly until 2070 concerning soils influenced by ground water and by stagnant water and at sites on steep slopes (> 25%) and on southerly slopes (120–240°).

• **Conclusion** The model allows mapping of mean soil moisture at the national and regional scale as shown by the example of Germany and the Kellerwald National Park across observed periods and climate scenarios. It should be combined with available ecological data on forest ecosystem types (Jenssen et al. 2013; Schröder et al. 2015) and tested at the European scale.

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Contribution of the co-authors

Winfried Schröder headed the investigation and drafted the manuscript. Stefan Nickel developed and applied the GIS-integrated fuzzy rule-based model.

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1 Introduction

Climatic changes are likely to have impacts on structures and functions of ecosystems and, thus, to change biodiversity (Dury et al. 2011). Climate change, in terms of temperature increase, seasonality and precipitation regimes, is currently observed and, according to projections, will continue or even be strengthened over the twenty-first century. Climate change is and will be possibly characterised by an increase in annual mean temperature and change in rainfall pattern with alternating dry periods and periods of heavy rainfall (Christensen et al. 2007; Stocker et al. 2013). This raises the question on the availability of water for plants which does not only depend from the precipitation amount and temperature but also on the physical and chemical characteristics of the soils and the depth of soil accessible to the roots (De Cáceres et al. 2015). In temperate forests, reduced water availability and drought stress could severely affect forest growth and nutrient cycling (Bréda et al. 2006; Ciais et al. 2005; Gessler et al. 2004; Rennenberg et al. 2006). Drought stress could subsequently enhance the vulnerability of trees to fungal diseases and insect damages (Desprez-Loustau et al. 2006; Rouault et al. 2006). Furthermore, summer drought increases the risk of forest fire events (Williams et al. 2010) and changes in biodiversity (Archaux and Wolters 2006). Thus, faced with climate change, ecological assessments of forest ecological integrity and services in forest management and nature conservation need estimations of current and future soil moisture (Calder 2007; Jenssen et al. 2013; Pilaš et al. 2011; Schröder et al. 2015; Schwärtzel et al. 2011; Wahren and Feger 2011). This is of particular interest for estimating shifts in forest species composition or adaptation and mitigation strategies such as “climate-adaptive forests” (De Cáceres et al. 2015; Jenssen 2009; Lindner et al. 2010).

Several methodological approaches exist for determining soil moisture. Some modelling approaches were reviewed by Saint-André et al. (2014) focusing on soil-plant interactions. Soil moisture modelling tools often are based on quantitative, empirical and statistical approaches (Einecke 2005; Scheinost 1995) or ordinations (Benzler et al. 1987; Hofmann 2002; Marks 1979; Zepp and Müller 1999). Modelling approaches usually compute soil water from a water balance model taking into account inputs (rainfall), outputs (evapotranspiration, drainage) and changes in soil humidity. The actual soil humidity results from this balance, whereby maximal humidity depends on soil depth and physical properties. Quantitative approaches rely on measurements of physical properties of soils such as water tension and water content (Topp et al. 1980; Menziani et al. 1996) or remote sensing of soil moisture content (Hirschi et al. 2014; Zeng et al. 2016), whilst qualitative approaches are based on pedological or ecological ordination of soil moisture. Pedological soil moisture classes are defined based on, e.g. the ground water level, soil texture, soil type

and long-term averaged climatic water balance (AG Boden 1982; Benzler et al. 1987). Ecological soil moisture classes are differentiated using vegetation complexes as indicators for long-term averaged soil moisture (Dahmen et al. 1976; Ellenberg et al. 1991; Hofmann 2002). Due to small-scale variability of soil moisture (Western et al. 2002) and since in situ measurements and dynamic modelling provide only local information, the potentials for regionalisation of soil moisture here are typically low. On the other hand, remote sensing approaches provide data on the uppermost millimetres or centimetres of the soil and in dependence on the sensor at a spatial resolution of between 1 and 50 km (Hasenauer et al. 2009).

For evaluations of impacts on biodiversity or ecological integrity and, respectively, potential forest development exposed to climate change and soil moisture deficits, a forest classification was developed and applied at the national scale (1:500,000) and at the regional scale (1:25,000) by example of Germany and the Kellerwald National Park (Jenssen et al. 2013; Schröder et al. 2015). Jenssen et al. (2013) also modelled changes in soil moisture with MetHyd which is part of the VSD modelling tool (Posch and Reinds 2009). This process-based dynamic modelling of soil moisture is rather extensive regarding the data needed (Jenssen et al. 2013; Schröder et al. 2015, 2017). Therefore, the model was applied for site-specific modelling only. For spatio-temporal assessments of climate change-induced impacts on ecological integrity and services, spatio-temporal information on soil moisture was needed, which enables being linked with data on forest ecosystems (Jenssen et al. 2013; Schröder et al. 2015), available nation-wide and on the regional scale as mentioned above.

For calculating spatially and temporally differentiated data, we decided for a fuzzy rule-based modelling approach. It is based on the rule-based model as published by Benzler et al. (1987) which was made available online through Müller and Waldeck (2011) and which was enhanced by Ad-Hoc-AG Boden (2006a, b). The rule-based model is characterised by discontinuous, categorical or ordinal data. Therefore, the model to be developed in this investigation was complemented by fuzzy logic (Bardossy and Duckstein 1995; Cullum et al. 2016; Peters et al. 2011; Zadeh 1978) to cope with continuous data (climatic water balance, gradient and cardinal point of slope, silt and clay content, depth to ground water table). The use of fuzzy sets allows for modelling flowing transitions between categorical variables. By this, a loss of information can be diminished when using surface covering quantitative data on pedologic, hydrologic and climatic input parameters (Table 1, column 2).

In addition to the estimation and mapping of soil-moisture at the national and regional levels, this

investigation aimed at a compilation of the soil moisture classification of Benzler with that of Hofmann (2002). The latter one was used for the forest typology which was developed to evaluate potential alteration in Germany's forests state due to changes of climate and nitrogen deposition (Jenssen et al. 2013; Nickel et al. 2015; Schröder et al. 2015).

In essence, this investigation aims to spatio-temporally estimate ecological soil moisture according to Hofmann (2002) at both the national and regional levels (exemplified for Germany and the Kellerwald National Park), to statistically analyse temporal trends of modelled soil moisture for the time period 1961–2070, to map soil moisture changes (drying-out) on both spatial scales, and thus, to create a basis for further spatio-temporal evaluations of impacts on biodiversity or ecological integrity and, respectively, potential forest development exposed to climate change and soil moisture deficits based on available spatial data on forest ecosystems (Jenssen et al. 2013; Schröder et al. 2015).

2 Materials and methods

2.1 Rule-based mapping of soil moisture

A rule-based method for modelling soil moisture was developed based on a pedologic approach (Benzler et al. 1987; Müller and Waldeck 2011). It enables the approximation of soil ordinated moisture classes or categories using widespread available quantitative data on the following pedologic, hydrologic and climatic input parameters: soil groups distinguished by main water regime (Table 1), soil texture classes each specified by field water capacity in the rooted soil horizons ($n = 7$) (AG Boden 2005), averaged mean soil water table, degree of stagnant water, climatic water balance during the period March–October, gradient and cardinal point of slope. The modelling tool developed was applied at the national scale by example of Germany and at the regional scale by example of the Kellerwald National Park using the data given in Table 1. The climate during 1961–1990, 1991–2010, 2011–

Table 1 Data needed for calculating pedological and ecological soil moisture categories according to Benzler et al. (1987) and Hofmann (2002), respectively

Rule-based modelling of pedological soil moisture ordination (Benzler et al. 1987)	Fuzzy-rule-based modelling of ecological soil moisture ordination (Hofmann 2002)	Derivation, source
Climate		
Climatic region; 8 regions (Müller and Waldeck 2011)	Climatic water balance March–October [mm]	Derived from the annual average amount of precipitation/evapotranspiration as published by DWD and calculated with the regional climate change model STAR II
Relief		
Gradient of slope divided into 7 categories (KA5, Tab. 6)	Gradient of slope [%]	Calculated by use of SRTM-DEM
Cardinal point of slope divided into 8 categories (KA5, p. 59)	Cardinal point of slope [°]	Calculated by use of SRTM-DEM
Soil		
Soil classification; 4 soil groups*	Soil classification; 4 soil groups*	Taken from BÜK1000 and BFD50
Soil texture categories (KA5, Tab. 30)	Silt content [Mass%] Clay content [Mass%]	Taken from BÜK1000 and, respectively, from BFD50 Hessen
Effective field water capacity 0–1 m divided into 6 categories (AG Boden, 2006a, b)	Effective field water capacity 0–1 m [mm]	Derived for each soil texture horizon from BÜK1000 and, respectively, BFD50 Hessen
Soil moisture divided into 7 categories (KA3, Tab. 55)	–	Taken from BÜK1000 and BFD50 Hessen
Stagnant water divided into 7 categories (KA3, Tab. 56)	–	Derived according to KA3, Tab. 56 and KA5, Tab. 61 from soil organic matter content of surface soil, taken from BÜK1000 and, respectively, BFD50 Hessen
Soil water table divided into 7 categories (KA5, Tab. 59)	Average depth to ground water table [dm]	Taken from BÜK1000 or derived from KA3 (Tab. 55) and KA5 (Tab. 60) based on soil moisture and soil texture (BFD50 Hessen)

BFD50 Hessen = soil map of Hesse (1:50,000); BÜK1000 = National soil map of Germany (1:1,000,000); DWD = Deutscher Wetterdienst; KA3 (AG Boden 1982); KA5 (Ad-Hoc-AG Boden 2005); SRTM-DEM = digital elevation model derived from the Shuttle Radar Topography Mission (SRTM). <http://www2.jpl.nasa.gov/srtm/cbanddataproducts.html> (download 01.09.2015); STAR II = STATistical Regional model STAR II (RCP8.5)

*(1) Soils influenced by ground water, (2) soils with stagnant water, (3) peat bogs and fens, (4) other terrestrial soils

2040 and 2041–2070 was parameterised by the climatic water balance March–October [mm] using the annual average amount of precipitation and FAO reference evapotranspiration (DWD) and a respective climate scenario calculated with the regional climate change model STAR II (RCP8.5) developed by the Potsdam Institut für Klimafolgenforschung (PIK) (Orlowsky et al. 2008). For statistical regionalisation, temporal trends of temperature from global climate projections as well as observed values from climate stations (DWD) were used (ibid.). For the Kellerwald National Park, a correction of the climatic water balance was calculated according to rule base VKR 3.30 (Ad-hoc-AG Boden 2006a) with regard to gradient and cardinal point of slope using the digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM) with a spatial resolution of 90 m.

2.2 Consolidation of pedological and ecological soil moisture categories

In many cases, classifications such as soil moisture ordinations like the pedological one from Benzler et al. (1987) and the ecological one developed by Hofmann (2002) use the same words with different meanings (Zepp 1995). In Table 2, we assigned their categories semantically. This semantic procedure was then corroborated with metric data by spatially referencing the nation-wide map of ecosystem types (Jenssen et al. 2013; Schröder et al. 2015) which includes information about the respective ecological soil moisture class with the German soil map BÜK1000 and the related soil moisture class for 1961–1990 according to Benzler et al. (1987).

2.3 Fuzzy rule-based modelling of soil moisture according to Hoffmann (2002)

The approach of Benzler et al. (1987, in: Müller and Waldeck 2011) encompasses rules for linking the information needed to ordinate soil moisture classes, whereby the assignment of continuous data such as the climatic water balance or the content of clay and silt to ordinated classes causes a loss of information. This could be diminished by application of fuzzy logic.

In Boolean logic, a set G includes a definite number of elements e . Each element e is a member of G ($e \in G$) or not ($e \notin G$). Such sets are called crisp sets (Lippe 2006) which can be exhaustively described by a membership function μ . The values of that function are called membership degrees $\mu(x)$ and only can have the values 0 or 1. The fuzzy set theory enables to define functions between 0 and 1 (Lippe 2006). Accordingly, e may only partly belong to one or several fuzzy sets G . Typical membership functions are singletons as well as triangle, trapeze and Gauß functions (Beierle and Kern-Isberner 2006).

The fuzzy inference process includes the fuzzification of all input values into fuzzy membership functions, the execution

Table 2 Compilation of pedological and ecological soil moisture categories according to Benzler et al. (1987) and Hofmann (2002), respectively

Pedological soil moisture ordination (Benzler et al. 1987)	10—wet	9—very moist	8—moist	7—slightly moist	6—very fresh	5—fresh	4—slightly fresh	3—slightly dry	2—dry	1—very dry	0—roughly dry
Ecological soil moisture ordination (Hofmann 2002)	10—11—overflooded wet	9—10—very wet	8—9—wet	7—8—moist moist	6—7—moderately moist	5—6—fresh	4—5—moderately fresh	3—4—moderately dry	2—3—dry	1—2—very dry	0—1—extremely dry

of all applicable rules in the knowledge/rule base to compute the fuzzy output functions and the defuzzification of the fuzzy output functions to get crisp output values (Kiendl 1997; Kruse et al. 1993; Lippe 2006) (Fig. 1). By this, fuzzy logic enables fuzzy reasoning within an inference process operating as *fuzzy rule-based systems*. Such systems can be used to model real transitions which in the model from Benzler et al. (1987) were represented as crisp borders between soil moisture categories (Bardossy and Duckstein 1995; Borgelt et al. 2003).

To quantify soil moisture values according to the ecological approach of Hofmann (2002), a fuzzy rule-based model was developed using information on different types of soil, influence of ground water and stagnant water, and in particular metric data on clay (T) and silt (U) percentage, climatic water balance (CWB) March–October, and averaged depth to ground water table (GW). Additionally, for adjusting the climatic water balance, gradient and cardinal point of slope were calculated by the use of the DEM (Fig. 2).

The combination of fuzzy logic and the classification of soil moisture according to Benzler et al. (1987, in: Müller and Waldeck 2011) and Hofmann (2002) enables to model fuzzy transitions between crisp soil moisture classes. For modelling the climatic regions (KB; eight regions) and the ground water classes (GWS, seven categories), triangle functions were applied in a way the degrees of membership summing up to 1. The soil texture categories were modelled using triangle and trapeze functions. For terrestrial soils of the fourth group (Table 1), the categories of effective soil water content in the soil column 0–1 m (EFWC) were modelled according to linkage rule VKR 4.14 (Ad-hoc-AG Boden 2006b) by the use of triangle functions. Since all input variables influence the soil moisture, all membership functions were combined by logical AND. Rules were given equal weight (degree of support, DoS = 1.0) and memberships of rules with the same conclusion were combined by bounded sum. The membership functions of the pedological moisture ordination (Benzler

et al. 1987) cover the ecological soil moisture ordination (Hofmann 2002) according to Table 2 enabling a vice versa transformation of both ordinations within the defuzzification process. The classes of gradients and cardinal points of slopes were represented by triangle functions. The defuzzification was realised by fuzzy mean operations (IMSE-CNM 2012) using all output values multiplied with the respective degree of membership.

The fuzzy rule-based system comprises 60 input fuzzy sets representing categorical values of 6 input variables, 37 output fuzzy sets for 4 output variables and 7407 rules within 4 rule bases according to Benzler et al. (1987, in: Müller and Waldeck 2011) and Ad-Hoc-AG Boden (2006a, b). An overview of the whole fuzzy rule-based model is given in the Supplement (Figs. S1–S19). The fuzzy logic reasoning should now be exemplified through the use of four rules and data from a site which is influenced by ground water (Fig. 3):

For fuzzification, a CWB of -40 mm was assigned the climatic region KB2 with degree of membership $\mu(\text{CWB}) = 0.7$ and KB3 with $\mu = 0.3$, a distance from the ground water table (GW) of 2 dm was assigned to ground water level (GWS) ‘extremely high’ and ‘high’ with each $\mu(\text{GW}) = 0.5$, a silt percentage of $U = 5\%$ was assigned to class ‘0–10%’ with $\mu(U) = 1.0$ and a clay percentage of $T = 3\%$ was assigned to class ‘0–5%’ with $\mu(T) = 1.0$.

The fuzzification effects a decomposition. Thus, in the fuzzy inference process, four rules (R1–R4) according to Benzler et al. (1987) are evaluated in parallel (Table 3):

- R1. IF KB = 2 AND GWS = ‘extremely high’ AND U = 0–10% AND T = 0–5% THEN Moisture = 8 (‘moist’)
- R2. IF KB = 2 AND GWS = ‘high’ AND U = 0–10% AND T = 0–5% THEN Moisture = 7 (‘slightly moist’)
- R3. IF KB = 3 AND GWS = ‘extremely high’ AND U = 0–10% AND T = 0–5% THEN Moisture = 9 (‘very moist’)
- R4. IF KB = 3 AND GWS = ‘high’ AND U = 0–10% AND T = 0–5% THEN Moisture = 8 (‘moist’)

Fig. 1 Scheme of a fuzzy rule-based system (modified according to Lippe 2006). Similar in Kruse et al. (1993), Strietzel (1996) and Kiendl (1997)

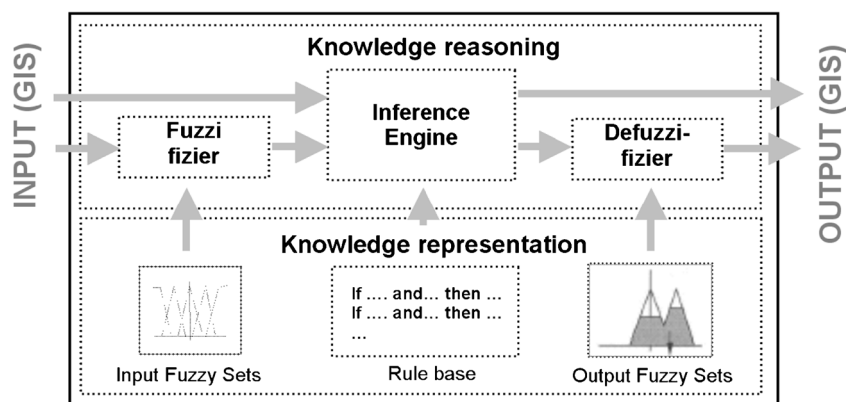


Fig. 2 Data flow within the fuzzy rule-based models for estimating ecological soil moisture according to Hofmann (2002)

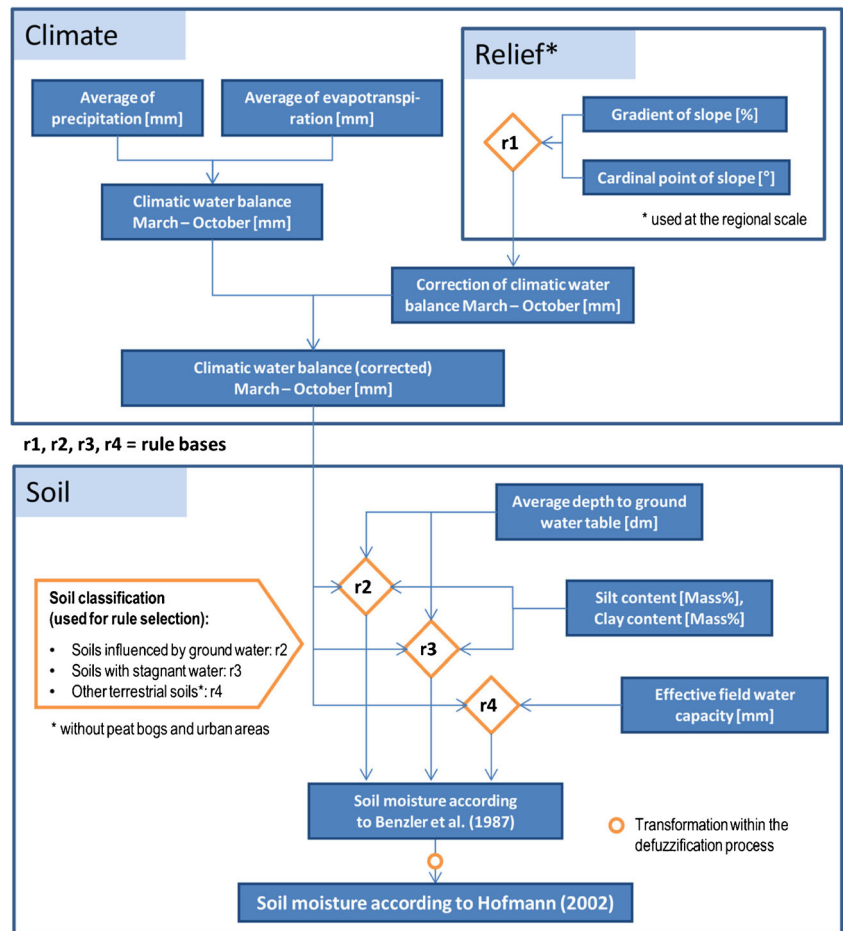


Fig. 3 Fuzzification of four ratio-scaled input values variables (x) exemplified through the use of eight membership functions quantifying the membership degrees (μ) to eight fuzzy sets representing the ordinal-scaled ‘rule input’

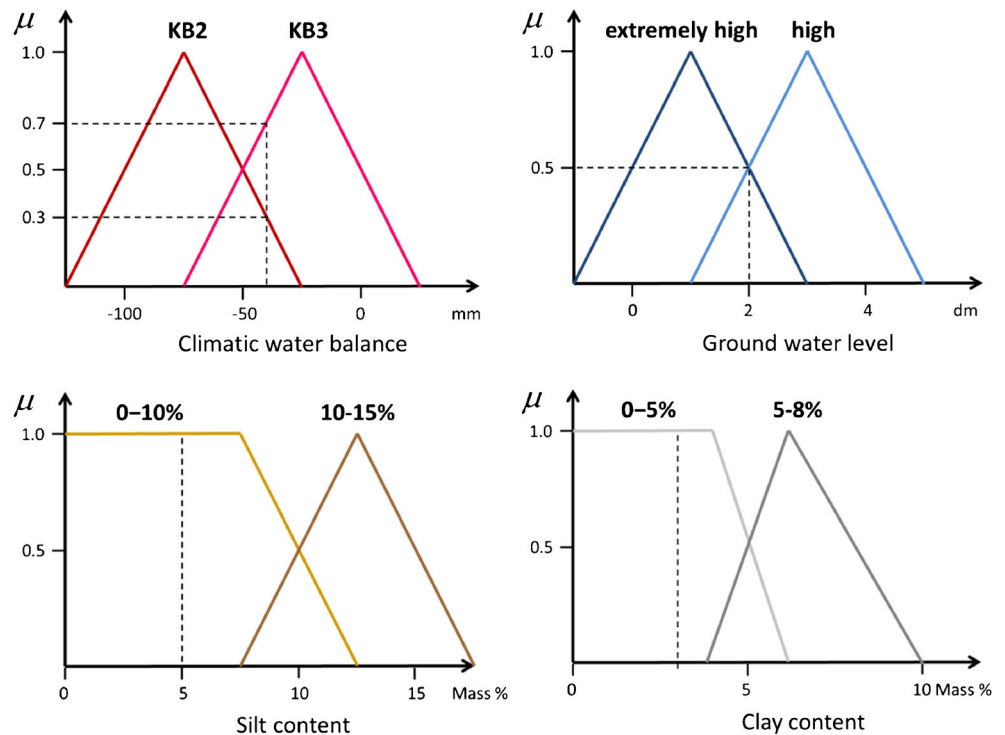


Table 3 Excerpt from the rule base (12 of 7407 rules) of the GIS-integrated fuzzy system to derive soil moisture values according to Benzler et al. (1987) as a basis for transformations to soil moisture values according to Hofmann (2002)

Rule base					
If				Then	
KB	GWS	Silt	Clay	DoS	Moisture
2	Extremely high	40–50	30–35	1.00	10
2	High	50–55	25–30	1.00	9
2	Extremely high	35–40	0–5	1.00	9
2	High	50–55	35–45	1.00	9
2	Extremely high	0–10	0–5	1.00	8
2	High	0–10	0–5	1.00	7
3	Extremely high	0–10	0–5	1.00	9
3	High	0–10	0–5	1.00	8
3	Extremely high	35–40	0–5	1.00	9
3	High	50–55	25–30	1.00	9
3	Extremely high	40–50	30–35	1.00	10
3	High	50–55	35–45	1.00	9

KB = climatic region; GWS = ground water level; Silt content [Mass%]; Clay content [Mass%], DoS = degree of support (weight factor); Moisture = soil moisture values according to Benzler et al. (1987)

In the rule base, the input variables were aggregated by multiplying the membership degrees of the input fuzzy sets which realises a fuzzy logical AND for calculating $\mu(R)$ (= membership degree of the rule) (Eq. 1):

$$\mu(R) = \mu(CWB) * \mu(GW) * \mu(U) * \mu(T) \tag{1}$$

This leads to four memberships of four rules calculated within the fuzzy inference process:

$$\begin{aligned} \mu(R1) &= 0.3 * 0.5 * 1.0 * 1.0 = 0.15 \\ \mu(R2) &= 0.3 * 0.5 * 1.0 * 1.0 = 0.15 \\ \mu(R3) &= 0.7 * 0.5 * 1.0 * 1.0 = 0.35 \\ \mu(R4) &= 0.7 * 0.5 * 1.0 * 1.0 = 0.35 \end{aligned}$$

Rules with the same conclusion are then combined by bounded sum (Eq. 2):

$$\mu(x, y) = \min(1.0, x + y) \tag{2}$$

Thus, the conclusions from all rules applied are composed as follows:

$$\begin{aligned} 7 \text{ (‘slightly moist’)} : \mu(R2) &= 0.15 \\ 8 \text{ (‘moist’)} : \mu(R1, R4) &= \min(1.0; 0.15 + 0.35) = 0.5 \\ 9 \text{ (‘very moist’)} : \mu(R3) &= 0.35 \end{aligned}$$

Finally, the defuzzification transfers the multiple output fuzzy sets to a single crisp output value. The fuzzy mean operator calculates the output as the sum of output values multiplied with their respective membership. This provides soil moisture information (DKF) according to Hofmann (2002) as a metric outcome.

$$\begin{aligned} DKF &= Mean(DKF(\text{‘slightly moist’}) * \mu(R2) + Mean(DKF(\text{‘moist’}) * \mu(R1, R4) + (Mean(DKF(\text{‘very moist’}) * \mu(R3))) \\ &= (6.9 * 0.15) + (7.5 * 0.5) + (8.5 * 0.35) = 7.76 \end{aligned}$$

As can be seen in Fig. 4, the transformation of both soil moisture ordinations within the defuzzification process was realised by defining the pedological ordination (Benzler et al. 1987) as output fuzzy sets and the ecological ordination (Hofmann 2002) as output variable.

2.4 Integrating the fuzzy rule-based model of soil moisture into a geographic information system (GIS)

The combination of the fuzzy approach explained above with a GIS should enable the spatial explicit modelling and mapping of soil moisture according to Hofmann (2002). Thereby, the GIS is used to model the spatial input data information needed for modelling as well as the mapping of the respective results. The fuzzy model was implemented by the use of *Xfuzzy* 3.3 (IMSE-CNM 2012) which can be, after conversion to a Dynamic Linked Library (DLL), integrated into a user-defined tool for ESRI ArcGIS 10.2 used for processing spatial data and for model calculations (Fig. S20 in the Supplement).

The fuzzy modelling and mapping of the soil moisture according to Hofmann (2002) was performed for 1961–1990, 1991–2010, 2011–2040 and 2041–2070 at the national scale for the territory of Germany as well as at the regional scale by example of the Kellerwald National Park located in the German federal state Hesse (Figs. 5, 10). The data used are given in Table 1, column 2. Peat bogs and urban areas were

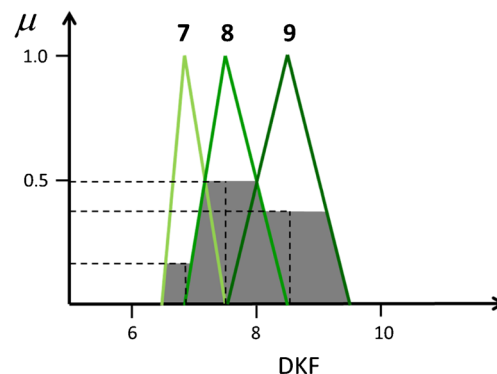


Fig. 4 Defuzzification of three output fuzzy sets transforming soil moisture values according to Benzler et al. (1987) to those according to Hofmann (2002)

excluded due to excessive model uncertainties and, respectively, missing soil data.

2.5 Model validation

Model validation was processed to determine the degree to which the model results represent the real system. The quantification of the statistical relationship between modelled data and respective ecologically indicated soil moisture according to Hofmann (2002) aimed at assessing the model quality and, respectively, performing a bias correction by calibrating the model results with information on the real system. After bias correction, a Wilcoxon signed-rank test (Wilcoxon 1945) was carried out with $\alpha = 0.05$ to assess whether medians of corrected fuzzy-modelled and ecologically indicated soil moisture values are significantly equal. Data on 20-year average soil moisture, modelled for the area of the Kellerwald National Park (time period 1991–2010), and ecological indicator values of the soil moisture based on vegetation samplings in the Kellerwald ($n = 95$, 2007–2009) were used. Indicator values for moisture according to Hofmann (2002) were derived by a vegetation-based indicator model (Jenssen et al. 2010; Schröder et al. 2015). Since the 3-year ecological indicator values characterise the long-term, mean soil moisture status (Ellenberg et al. 1991), it is assumed that the vegetation data approximately represent the period 1991–2010. For quantifying the goodness-of-fit, i.e. how well the model fits the mean species indicator values ($n = 95$), coefficient of determination (R^2) was determined as well as root mean squared error (RMSE) and mean absolute error (MAE) according to Eqs. 3 and 4.

$$RMSE = \sqrt{\text{Mean}((x-y)^2)} \quad (3)$$

$$MAE = \sum(|x-y|)/n \quad (4)$$

with x = fuzzy-modelled soil moisture (DKF), y = indicated soil moisture (DKF), Mean = arithmetic mean and n = sample size.

2.6 Statistical analysis

The statistical analysis of the modelling results included a comparison of statistical numbers for the four time intervals mentioned above derived by descriptive statistics, trend analyses according to Mann-Kendall (Mann 1945; Kendall 1975) as well as by difference maps for 1961–1990 and 2041–2070 quantifying the amount and trend direction of the modelled results. Since the sample size was small ($n = 4$), temporal trends could only be tested at a significance level of $\alpha = 0.1$. The amount of

soil moisture changes (drying-out) was classified as follows and mapped:

−0.1	to	−0.4	=	very low
−0.5	to	−0.9	=	low
−1	to	−1.4	=	medium
−1.5	to	−1.9	=	high
< −2			=	very high

3 Results

3.1 Model validation

The species indicator values according to Hofmann (2002) predominantly from vegetation sampling sites, which are not influenced by ground water or stagnant water within the Kellerwald National Park (Fig. 5), range between DKF 2.0 (= dry) and 7.6 (= moist). The median amounts to DKF 5.3 (= fresh).

These indicator values and the modelled mean soil moisture are significantly correlated with Spearman's rank correlation coefficient (r_s) = 0.39 ($p < 0.01$) and Pearson's correlation coefficient (r_p) = 0.46 ($p < 0.01$). Ninety-five pairs of values, representing fuzzy-modelled and ecologically indicated soil moisture, revealed a positive, linear association between both variables, described by the statistical model according to the regression equation given in Fig. 6.

Coefficient of determination amounts to pseudo $R^2 = 0.21$, i.e. the regression model explains 21% of the variance. The range of validity is between 2.5 (= dry) $< x < 7.5$ (= moist). The models' systematic errors (biases) were statistically corrected by an application of the regression equation (Fig. 6) on the fuzzy-modelled average soil moisture (1991–2010). The corrected values with blanket coverage of the Kellerwald National Park are shown in Fig. 5. After bias correction, the medians of both, ecologically indicated and fuzzy-modelled soil moisture, were significantly equal (Wilcoxon signed-rank test, $p > 0.05$). The measures of the model validity amount to RMSE = 0.86 and MAE = 0.67. This signifies a mean deviation of half a moisture category to one moisture category according to Hofmann (2002).

3.2 Germany

The results of modelling average soil moisture according to Hofmann (2002) during 1961–1990, 1991–2010, 2011–2040 and 2041–2070 in Germany are given in Figs. 7 and 8. From the data the average soil moisture (DKF) can be expected to decline until 2070. According to the Mann-Kendall test, this trend is statistically significant ($p < 0.1$) for the soils influenced by ground water and stagnant water. Soil influenced by ground water show a medium to high decrease of average soil moisture

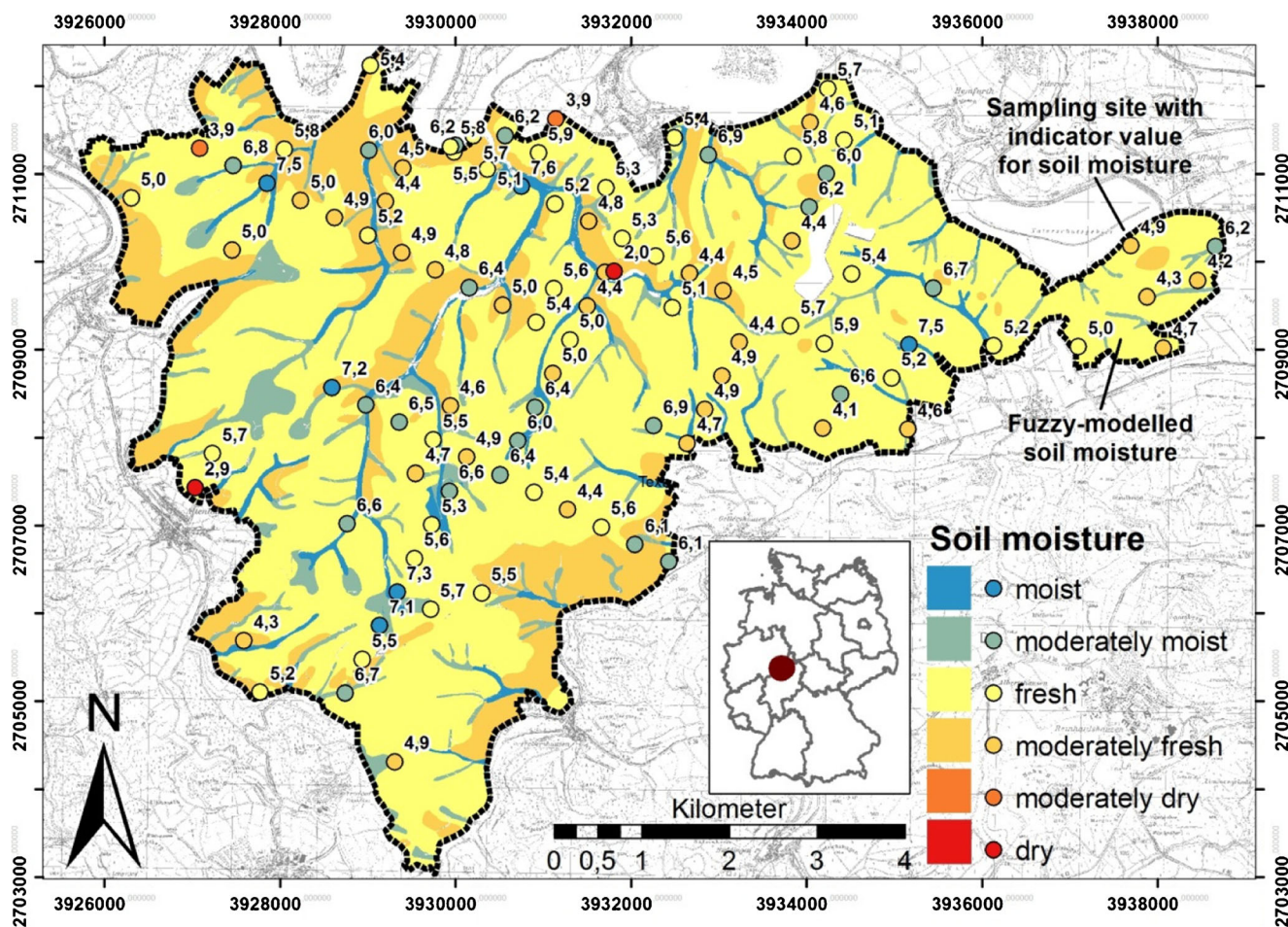


Fig. 5 Spatial distribution of fuzzy-modelled mean soil moisture (DKF) (1991–2010) according to Hofmann (2002) and respective indicator values calculated on data from vegetation samplings (2007–2009) in the Kellerwald National Park

corresponding to one and two categories until 2070. Soils which are characterised by stagnant water exhibit medium, high and very high decline. For other soils, medium to low decrease of soil moisture was calculated. Spatial hot spots of soil moisture

decrease covering at least 5% of the federal states could be observed in Bavaria, Hamburg, Hesse, Lower Saxony, North Rhine-Westphalia and Saxony. In Bavaria and Hesse, the estimated decline amounts by at least two categories.

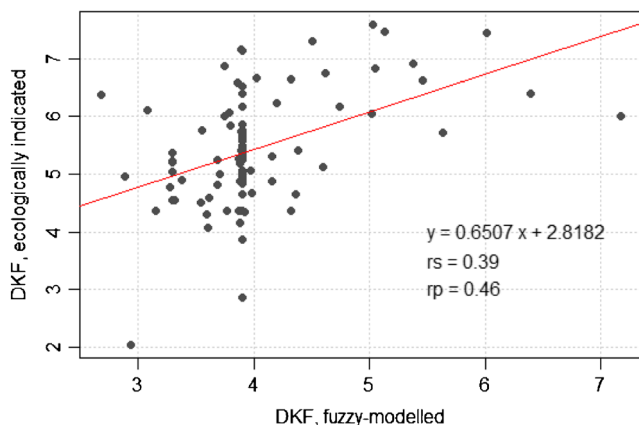
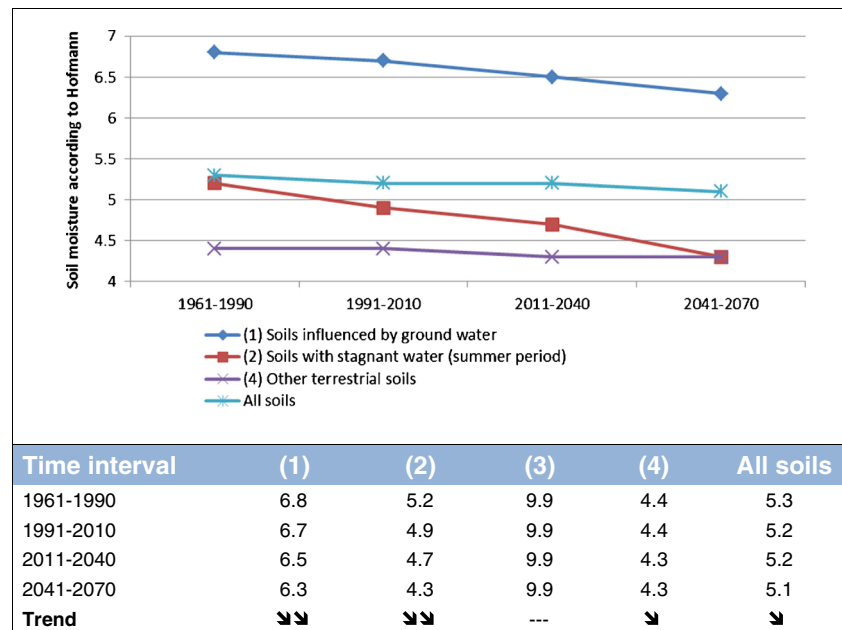


Fig. 6 Regression model quantifying the relationship between the fuzzy-modelled soil moisture (DKF according to Hofmann 2002) and respective species indicator values derived from 95 vegetation samplings in the Kellerwald National Park, r_s = SPEARMAN correlation coefficient, r_p = PEARSON correlation coefficient (cf. Fig. 5)

3.3 Kellerwald National Park

The temporal trend and spatial pattern of the estimated soil moisture across time are depicted in Figs. 9 and 10. Accordingly, the average soil moisture declines until the year 2070 in the Kellerwald National Park. This temporal trend is statistical significant ($p < 0.1$) for soils influenced by stagnant water. From 1961–1990 to 2041–2070, the soil moisture decrease is low on 19% of the Kellerwald area (–0.5 to –0.9 moisture categories) and medium (–1 to –1.4 soil moisture categories) on 1% of that region. Highest decreases are related to climate-induced declines of climatic water balance at sites influenced by stagnant water, in particular concerning the soil moisture degree in the summer season and, respectively, at sites on steep slopes (>25%) and on southerly slopes (120–240°).

Fig. 7 Temporal trends of fuzzy-modelled average soil moisture (DKF) according to Hofmann (2002) across time (1961–1990, 1991–2010, 2011–2040 and 2041–2070) in Germany (cf. Fig. 8)



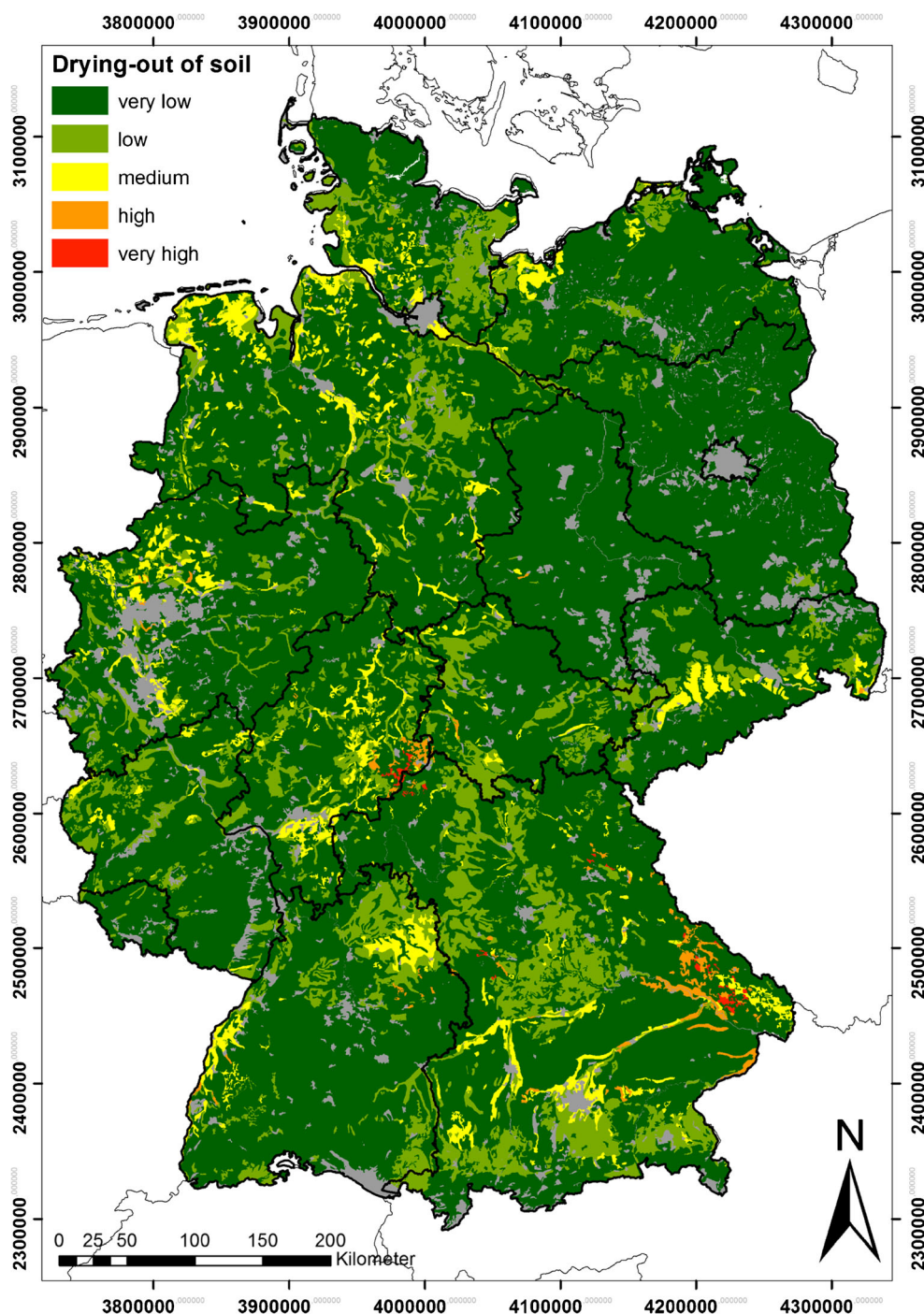
(1) Soils influenced by ground water, (2) Soils with stagnant water, (3) Peat bogs and fens, (4) Other terrestrial soils; Trend: ↘ = decline; ↘↘ = decline, statistically significant according to Mann-Kendall ($p < 0.1$)

4 Discussion

Action 5 of the EU Biodiversity Strategy to 2020 calls Member States to map and assess the condition (state) of ecosystems and their services in their national territory. Mapping and assessment of ecosystems and their services (MAES) should support the operationalisation of Action 5 (Burkhard and Maes 2017; Maes et al. 2013). In that context, due to the high potential of forests to supply ecosystem services (Maes et al. 2016) and regarding the high percentage of forest coverage in Europe (35%) and e.g. Germany (32%) (Forest Europe 2011; Kempeneers et al. 2011), the condition of forests is one of the major issues. Soil moisture is an essential environmental characteristic related to climate change and affecting spatial patterns and trends of forest condition throughout time. Based on a forest typology derived from data collected in 21,600 forest stands across Germany, an approach to assess and map the condition of forests was developed (Jenssen et al. 2013; Schröder et al. 2015). However, the development of forest soil moisture in areas of large spatial extent such as a national park or the whole territory of Germany could not be estimated. This investigation examined whether fuzzy modelling and mapping of soil moisture for observed periods and climate scenarios could be an alternative for dynamic modelling at the national and regional scale. The respective method, developed by example of Germany and the Kellerwald National Park, and the results yielded are appraised in the subsequent section with respect to eligibility, assets and drawbacks of the fuzzy logic approach and the quality of the results.

The fuzzy logic approach used to model and map soil moisture for observations and future climate scenarios is not fuzzy but a precise logic of imprecision and approximate reasoning (Zadeh 2008). Fuzzy logic was used to formalise the reasoning and decisions based on imprecise, uncertain, incomplete and conflicting information (Cullum et al. 2016; Zadeh 2008, p. 2751) and, in particular, categorical information on continuous geographical phenomena (Peyke and Wolf 1999). The fuzzy rule-based model enables an approximation of ecologically defined scenarios of soil moisture (Hofmann 2002) with a few nation-wide and regional area covering data on characteristics of soil, soil hydrology and climate. Based on the fuzzy theory (Zadeh 1965, 1978), the model also includes a pedologic soil moisture ordination (Benzler et al. 1987) and allows for modelling flowing transitions between soil moisture categories of both ordinations. By this, a loss of information can be diminished when using quantitative data on pedologic, hydrologic and climatic input parameters (Table 1, column 2). The application of fuzzy logic is similar to linear interpolation of the ecological soil moisture (Hofmann 2002) on the national and regional spatial scale as well as across time (1961–2070). By this, the modelling yields surface covering information going beyond the site level for which dynamic modelling up to now was used to derive soil moisture values for climate scenarios (Jenssen et al. 2013; Schröder et al. 2015). For estimating soil moisture, a bias correction based on a sufficient set of vegetation when using quantitative data on pedologic, hydrologic and climatic input parameters (Table 1, column 2). In principle, data validity of the observations limits the quality of the bias correction. Model validation and bias correction were carried out by the use of a small set of

Fig. 8 Spatial patterns of the temporal trend of the modelled average soil moisture (DKF) (1991–2010) Hofmann (2002) from 1961–1990 to 2041–2070 in Germany (cf. Fig. 7)

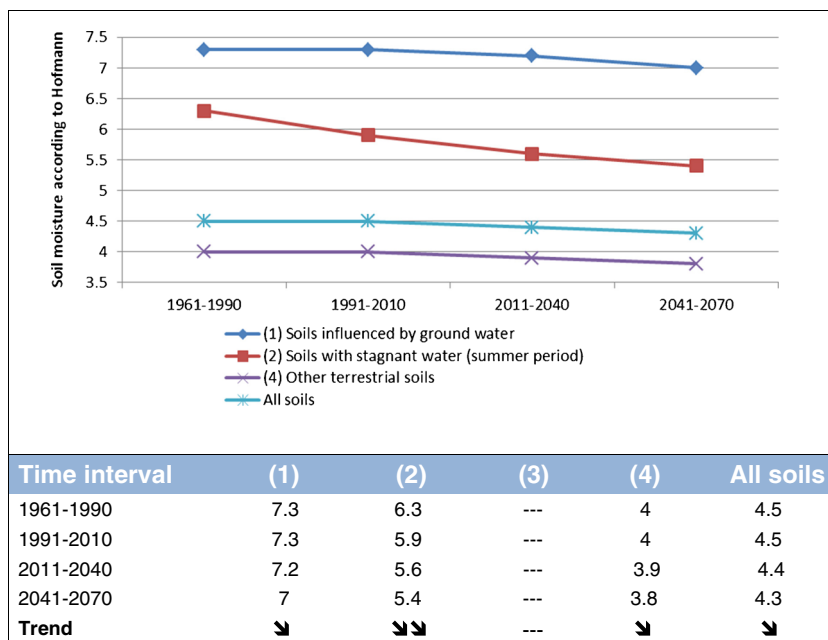


data from the Kellerwald National Park ($n = 95$), which is hardly representative for Germany as a whole, e.g. because the data were predominantly collected at sites, which are not influenced by ground water or stagnant water. Furthermore, it cannot be ruled out that the bias behaviour of the model changes over time and the results for future decades are based on climate change scenarios having notable intrinsic uncertainty.

Constraints of the modelling approach are the eligibility of model functions and structures mentioned above, the spatial

differentiation and generalisation of the data used as well as the grain of itemising the represented phenomena such as physical processes. The fuzzy operationalisation of the soil moisture approaches from Benzler et al. (1987) and Hofmann (2002) does neither regard the content of organic carbon (C_{org}) nor the density of dried mineral soils and lateral throughflow. However, the distance to the ground water table is considered, even at only a low differentiation and without regarding the impacts of climate change (Green et al. 2011; Jasper et al. 2006; Mosbrugger et al. 2012; Scibek and Allen

Fig. 9 Temporal trends of fuzzy-modelled average soil moisture (DKF) according to Hofmann (2002) across time (1961–1990, 1991–2010, 2011–2040 and 2041–2970) in the Kellerwald National Park (cf. Fig. 10)



(1) Soils influenced by ground water, (2) Soils with stagnant water, (3) Peat bogs and fens, (4) Other terrestrial soils; Trend: ↘ = decline; ↘↘ = decline, statistically significant according to Mann-Kendall ($p < 0.1$)

2006) as another factor of model uncertainty. This might be the main reason why peat bogs and fens did not show any temporal trend. However, it should be noted that 4 data points (time intervals) is the absolute minimum for the Mann-

Kendall test ($\alpha = 0.1$). In many cases, these are not enough points for trend detection, i.e. we might have an indication for a 'no trend' situation where there is one. For soils with stagnant water, the model developed only considers the soil

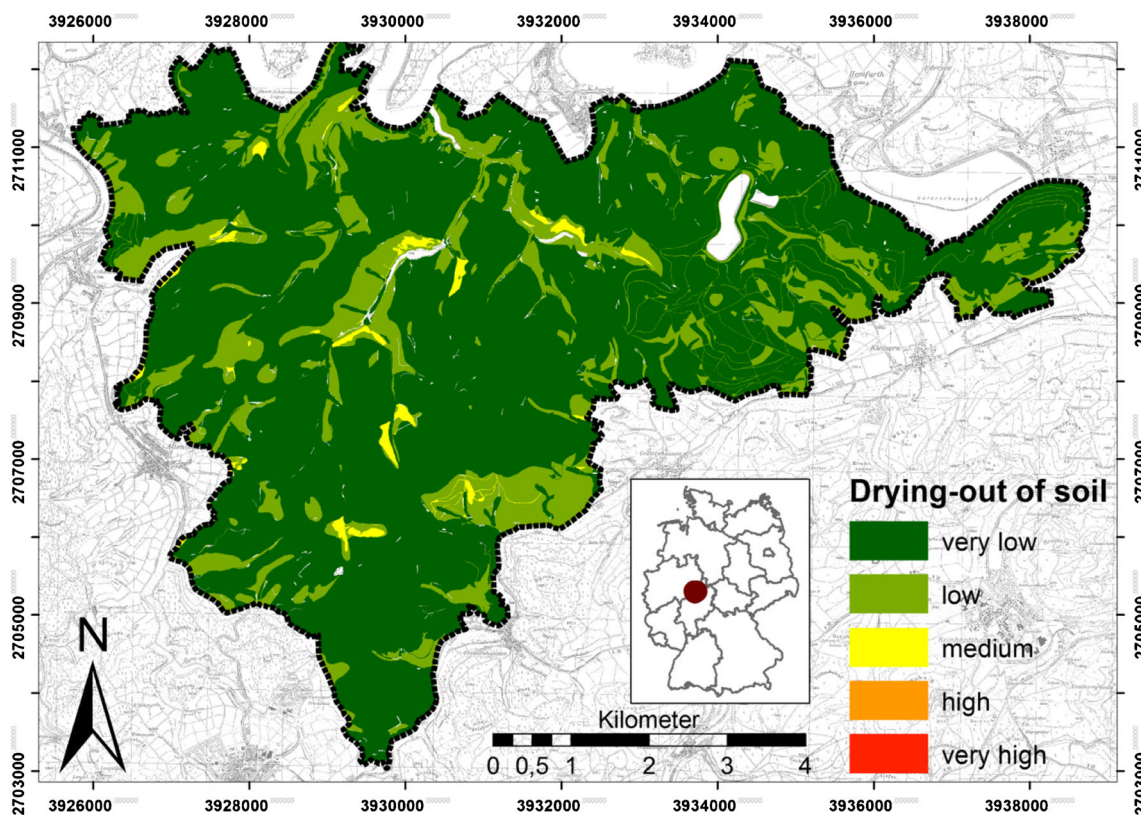


Fig. 10 Spatial patterns of the temporal trend of average soil moisture according to Hofmann (2002) between 1961–1990 and 2041–2070 in the Kellerwald National Park (cf. Fig. 9)

moisture from June to October, assuming the moisture in spring as constant. Rule-based VKR 4.14 (Ad-hoc-AG Boden 2006b) enables to estimate climate-induced changes of soil moisture for terrestrial soils not influenced by ground or stagnant water. This set of 18 rules considering climatic water balance and effective soil water content as predictors seems to be over-simplifying and thus should be supplemented by linkage rule VKR 3.30, Table 1 (Ad-Hoc-AG Boden 2006a) regarding the gradient and cardinal point of slope. Finally, the German national soil map BÜK1000 (BGR 2007) does not differentiate the sandy fraction in coarse, medium and fine which is of significance for the soil moisture regime. It is also important to keep in mind that the climatic water balance and, therefore, also the soil moisture are highly depending on land use, which is likely to increase the model's uncertainty.

Hence, the quality of modelling results strongly depends on the model structure and functions discussed above as well as on input data. This general statement is, for sure, true for the methodology developed and presented in this article. The assignment of the two basic schemes for deriving scenarios of ecological and pedological soil moisture (Hofmann 2002; Benzler et al. 1987) as shown in Table 1 and the subsequent fuzzy modelling is based on data at small cartographic scales (map on ecosystem types in Germany 1: 500,000, soil map of Germany 1: 1,000,000). Such cartographic scales necessarily are characterised by neglecting variation at the regional and local scale and, thus, extreme values, in particular since the ecological indication of soil moisture is based on plant species compositions under natural competition conditions which in space vary very widely (Ellenberg et al. 1991). Thus, for areas of large spatial extent, the detection of soil moisture changes throughout time should be more valid than estimations of the absolute value for the ecological soil moisture. This is in particular true when the model exhibits systematic errors (biases). However, the Kellerwald example corroborates that, if more detailed data are available, and a surface covering calculation of soil moisture is feasible at the regional scale. For the site level, process-based dynamic modelling is the method of choice.

5 Conclusion

This investigation enabled to spatio-temporally estimate soil moisture with available data covering the whole territory of Germany, to specify these estimates for the regional scale, to statistically analyse temporal trends of modelled soil moisture for the time period 1961–2070 and to locate soil moisture changes (drying-out) at both national and regional levels. The modelling results of soil moisture could be evidenced to be valid using empirical data on ecological soil moisture derived by vegetation analyses. Maps on spatial patterns and temporal trends calculated are meaningful and significant,

respectively. Hence, as shown for Germany and the Kellerwald National Park, fuzzy modelling and mapping soil moisture as climate change-related pressure for forest ecosystem integrity could be proved as eligible for assessments of areas of large spatial extents. Thus, it should be combined with available ecological data on forest ecosystem types (Jenssen et al. 2013; Schröder et al. 2015). The approach is generic if respective data are available so that it could be hypothesised to be easily reused and applied for other countries, at the European scale and for different European landscapes based on regionally scaled data on forest ecosystem types. This would help to map the condition of forests impacted by climate change and atmospheric deposition which are known as significant pressures for ecological integrity and related ecosystem services.

Data availability statement The data generated during and/or analysed during the current study are available from the corresponding author on reasonable request. It is planned that the data will be available in a repository.

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