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Fine-grained detection of land use and water table changes on organic soils over the period 1992–2012 using multiple data sources in the Drömling nature park, Germany

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ABSTRACT

The construction of consistent time series of land use presents a key challenge when accounting for elective land use-based activities under the Kyoto Protocol (wetland drainage and rewetting (WDR), cropland management (CM) and grazing land management (GM)), in which current land use-driven greenhouse gas emissions are compared to a reference situation in 1990.

This case study is the first to demonstrate the feasibility of using high-resolution land-use proxies from different datasets for Kyoto accounting in a data-rich case study region in Germany. The study region is characterised by organic soils and has been subject to significant nature conservation measures, including land-use changes, reductions in land-use intensity and changes in groundwater table depth.

A consistent time series of 20 years of land use with a spatial resolution of 0.01 ha was created from various fine-grained spatial datasets for organic soils in the Drömling nature park by applying a newly developed ‘translation key’. The translation key accounted for systematic differences in legends and thematic resolution. We also tested whether the land-use datasets served as trustworthy proxies for groundwater table depth.

Land use in the Drömling nature park became less intensive during the study period of 1992–2012. The greatest land-use change (142 ha year^{-1}, 1.14% year^{-1}) occurred between 2000 and 2008. This was in line with management measures undertaken in the nature park. The centre of the nature park became wetter and there was an increase in the share of grassland and more natural vegetation types.

The groundwater table correlated with land use and land-use intensity on organic soils in the study area throughout the entire period. Land-use changes were accompanied by altered groundwater tables, except for the conversion from cropland to grassland.

Our study indicates that detailed land-use time series can serve as a semi-quantitative proxy for groundwater depth, but that any robust quantitative assessment of water table changes requires *in situ* data, *e.g.* from a network of dipwells. Therefore, the combination of land-use and dipwell data provided an accurate basis for estimating GHG emission reductions from drained organic soils since 1990, which is the centre of the Kyoto activity WDR, but also part of afforestation/reforestation (AR) and deforestation (D), forest management (FM), CM and GM. Even the detailed land-use time series on its own would fulfil the requirements for WDR accounting, although with considerable uncertainty about the drainage status of the organic soils. We present the study area of organic soils as a showcase for combining the difficult issues of monitoring changes in land-use intensity as well as in soil wetness, the latter being most relevant for organic soils. The methodology is equally applicable to and relevant for mineral soils.

1. Introduction

Peatlands are important habitats for strongly specialised and endangered species and are therefore the subject of nature protection efforts (Joosten and Clarke, 2002; BMU, 2007). They are also

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hotspots of greenhouse gas (GHG) emissions when drained and used for agriculture or forestry (IPCC, 2014). The rewetting of peatlands efficiently reduces GHG emissions and may simultaneously restore multiple ecosystem services (Drösler et al., 2012; Joosten et al., 2013; Frank et al., 2014; Beyer and Höper, 2015).

The rewetting (*i.e.* reversal of drainage) of peatlands (or in other words organic soils) has been eligible under the Kyoto Protocol since 2008 as part of the activities forest management (FM), grazing land management (GM) and cropland management (CM), but it is an opportunity that has been largely overlooked. The rewetting of organic soils in all land-use categories has become a new eligible activity under the Kyoto Protocol since 2013, known as wetlands drainage and rewetting (WDR), which has increased the interest in accounting for emission reductions at a national level compared to the year 1990. At project level, reliable monitoring, reporting and verification (MRV) of emissions and emission reductions from organic soils opens up funding opportunities under voluntary carbon markets or other forms of payments for ecosystem services.

The key driver of GHG emissions from organic soils is the position of the groundwater table (Reddy and DeLaune, 2008), for which no nationwide maps are available. However, vegetation (Couwenberg et al., 2011), land use and land-use intensity are useful proxies for GHG fluxes (IPCC, 2014). Monitoring requires the detection of gross changes in land use and land-use intensity at adequate spatial and thematic resolution (Joosten et al., 2013; IPCC, 2014).

In Germany land parcels are typically very small and narrow in organic soils managed for agriculture due to their historical development (*e.g.* Oberbeck, 1957; Behre, 2008; Borsdorf and Bender, 2010). Thus fine-grained maps are needed to detect the small land parcels that may undergo changes in land use or management practices. Furthermore, no consistent time series of land-use datasets are available due to discontinuities in data sources. The data sources need to be combined using splicing techniques (IPCC, 2006, Vol. 1 Chapter 5), *i.e.* by overlap. This challenge is also frequently encountered elsewhere (Todorova et al., 2003; UNFCCC, 2013). A key challenge for Kyoto accounting and MRV efforts is to develop a methodology for consistent, robust time series of land-use changes by combining diverse data sources, despite their inherent differences.

The aim of this study was to contribute to improving MRV of GHG emissions by focusing on the most critical activity data. We introduced a new splicing technique (IPCC, 2006, Vol. 1 Chapter 5) to construct a consistent land-use time series by using a translation key technique to overlap land-use maps of diverging thematic and spatial resolution. The case study aimed to prove the feasibility of using land-use proxies for WDR monitoring in the data-rich region of the Drömling nature park, but the methodology is also applicable to other areas and even mineral soils. The Drömling nature park is a peatland area in Germany for which there is ample and detailed spatial information on land use, vegetation and water table available for different periods in the past.

The Drömling nature park has experienced land-use changes since the reunification of Germany in 1990. In the centre of the park, efforts have been made to establish wet, low-intensity grasslands on organic soils for nature conservation (Langheinrich et al., 2010). Two different fine-grained spatial products were used to create a consistent 20-year time series of land use and land-use intensity. We tested whether the datasets on land use were useful as proxies for groundwater table depth and whether they could serve to assess the success of rewetting measures in the Drömling nature park.

2. Material and methods

2.1. Definitions

The terms *peatlands* and *organic soils* are used interchangeably in this study, taking account of the most common terminologies. *Organic soils* are defined in a broad sense in line with the IPCC definition (IPCC, 2006, Annex 3. A.5) as soils with at least 12–18% soil organic carbon in the upper 20 cm, depending on clay content. Soil types were derived from a geological map (BGR, 2007). All mapping units of the geological map that approximately matched the IPCC definition of organic soils were included. This went beyond the national peat soil classification with an organic horizon of >30 cm and included more shallow organic soils similar to Histic Gleysols for example (for details see Roßkopf et al. (2015)).

The term ‘*land use*’ is used here for a classification of human activity that separates forestry, cropland and grassland, for example, according to the six broad IPCC land-use categories.

Land-use intensity is much finer and describes different classes of land use within a broad land-use category, such as high-intensity grassland or wet grassland. In this study, as far as possible we used information on intensity (secondary attributes of the land-use datasets) for broad land-use categories. Our data sources did not allow the detection of changes in fertiliser application, biomass export or grassland harvest dates. *Land-use intensity* is equivalent to classes of ‘*management practices*’ in IPCC terminology.

Gross land-use change covers all changes in land use and land-use intensity, *e.g.* from forest to grassland and from grassland to forest.

Net land use change shows the net balance of all changes in land use and land-use intensity, *e.g.* the net difference between all forest–grassland changes (for details, see ‘Methodological annex’ in Supplementary material).

2.2. Research area

The landscape area known as Drömling is located on the border of two federal states in Germany, Saxony-Anhalt and Lower Saxony. As more data are available for Saxony-Anhalt, the research area of this study was restricted to the large Drömling nature park in this federal state.

After 200 years of cultivation, the eastern part of Drömling was declared a nature park and hence a protected landscape area in 1990. In 2005, important areas for biodiversity were declared nature reserves (Langheinrich et al., 2010). The Drömling nature

Table 1
Properties of land-use maps and land-use information used in this study.

Dataset	Spatial Resolution	Temporal Accuracy	Positional Accuracy	Source
CIR 1992	<1:10.000	10 weeks	±0.5 m	LAU[a]
DLM 2000	<1:25.000	5 years to 3 months	±3 m	BKG[b]
CIR 2005	<1:10.000	11 weeks	±0.5 m	LAU[a]
DLM 2008	<1:25.000	5 years to 3 months	±3 m	BKG[b]
DLM 2012 (AAA[c])	<1:25.000	5 years to 3 months	±3 m	BKG[b]

[a] LAU—State Authority for Environmental Protection Saxony-Anhalt.
[b] BKG—Federal Agency for Cartography and Geodesy.
[c] AFIS-ALKIS-ATKIS.

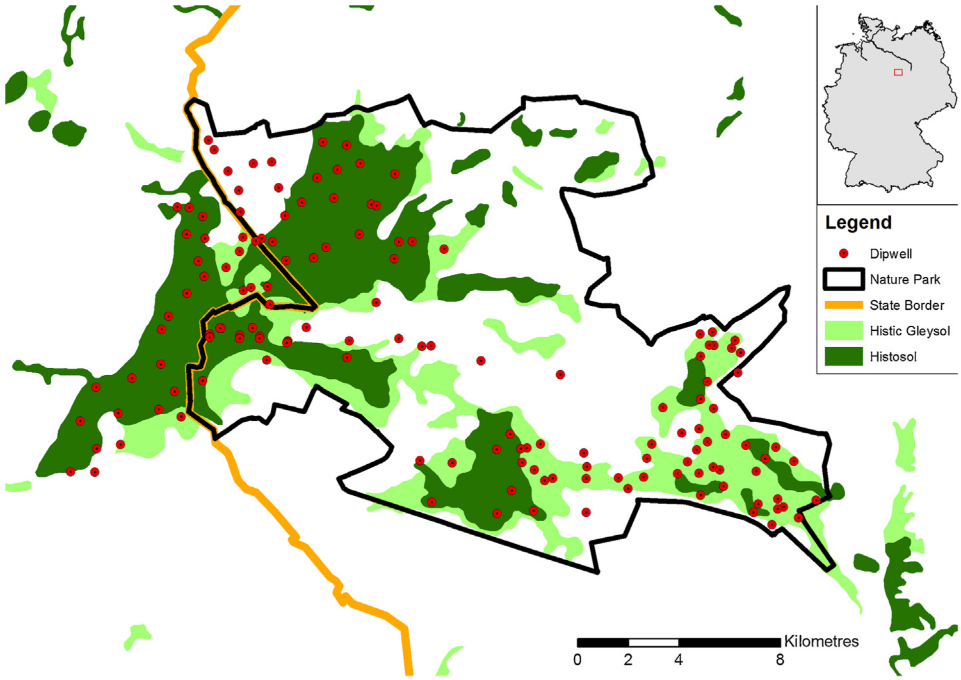

Fig. 1. Area of the Drömling nature park with organic soils and groundwater dipwells.
Dipwells and Nature Park: Naturparkverwaltung Drömling 2013, Soils (GÜK 200): BGR 2007, Basemap Germany: ESRI 2013.

park contains 12,758 ha of organic soils (Fig. 1), representing about 46% of the nature park and 0.6% of Germany's organic soils.

2.3. Data

2.3.1. Land use

In order to detect land-use change, five remotely-sensed datasets were used (Table 1):

- processed datasets from colour-infrared aerial photographs (CIR) of Saxony-Anhalt of 1992 and 2005
- the digital landscape model 'ATKIS Basic-DLM' (Authoritative Topographic-Cartographic Information Systems–Digital Basic Landscape Model) of 2000 and 2008
- the digital landscape model 'AFIS-ALKIS-ATKIS Basic-DLM' (official control point information system 'AFIS'–Authoritative Real Estate Cadastre Information System 'ALKIS'–Authoritative Topographic-Cartographic Information Systems 'ATKIS'–Digital Basic Landscape Model) (AAA-DLM) of 2012.

The datasets of the digital landscape model are referred to below as DLM. The DLM is updated continuously in time intervals (three months to five years). Updates depend on land-use classes (settlement and road infrastructure are desired to be most accurate in time) so that each dataset represents a mix of time stamps rather than the exact situation in the year of release (AdV, 2003).

Since 2012, the DLM has been based on the AAA model which has a slightly different classification compared to older DLM datasets. A direct semantic translation from the AAA model to the older ATKIS Basic-DLM was processed and validated, but is not explained further here. This semantic translation is also used in the German greenhouse gas inventory (UBA, 2014). We also used the attribute 'wet soil' from the DLM datasets. This attribute is applied to continuously water-saturated soils (AdV, 2003).

The various datasets differ in spatial resolution, temporal and spatial accuracy (Table 1), land cover/land use definitions and thematic detail. Furthermore, any remotely-sensed dataset has a certain interpretation and classification error, in particular in diversely structured, heterogeneous landscape parts or in land-use classes that can look temporarily quite similar (*e.g.* cropland and mown grassland). These systematic differences, inconsistencies and uncertainties between data sources and within data sources need to be accounted for to produce unbiased land-use change time series. This uncertainty was accounted for by data pre-treatment and by developing a 'translation key' of legends (see below and 'Methodological annex' in Supplementary material). The translation key overlapped the land-use categories of the CIR and DLM datasets representative of 2005–2008, which was the closest temporal match between the two data sources.

For grassland, six additional 'vegetation attributes' of the CIR datasets, such as 'high-intensity grassland', were considered for classifying land-use intensity.

2.3.2. Soils and terrain

The soil map used in this study is based on the general geological map of Germany 1:200 000 (BGR, 2007) (Fig. 1). A digital elevation model from a laser scan conducted in 1998 with a 5 m horizontal and 5 m vertical resolution was used. The uncertainty of the laser scan was 0.08 m (standard deviation of 0.11 m) (Landesamt für Landesvermessung und Datenverarbeitung, 1999).

2.3.3. Groundwater table

Data from 148 groundwater dipwells (93 on organic soils in the nature park) (Fig. 1), partially operating since 1992, were used to analyse groundwater table depths. Dipwells in the nature park were measured on average every twenty-five days. Dipwells outside the nature park were measured once a year. Furthermore, we used a map of the average groundwater table of the period 1993–2004, which is based on the water management model 'WBalMo Drömling' (WASY, 2004).

2.4. Land-use change detection

2.4.1. The grid sample approach

We applied the grid sample approach, which is one of the methodologies suggested by the IPCC to derive spatially explicit land use conversion data (Approach 3, IPCC, 2006, Chapter 3, Annex 3A.4). The grid sample approach is common practice in constructing national land-use change matrices for national GHG inventories in Europe (*e.g.* Germany, Portugal) (APA, 2013; UBA, 2014).

A 10 m × 10 m grid of data points was created to generate spatially consistent datasets. Each cross-sectional raster point of the grid represented one sample point (for further information see 'Methodological annex' in Supplementary material). One grid point represented 0.01 ha, which was smaller than the German definition of the minimum area of forest under the Kyoto Protocol (0.1 ha; UBA, 2014) and the smallest spatial unit definition for assessing land-use change (LUC) under the Kyoto Protocol (0.05 ha) and the minimum area of WDR of 1 ha (IPCC, 2003, 2014). The grid was dense enough to detect LUC in the study region, where land property is split into small, long parcels of *e.g.* 10 m × 50 m. At the same time, the chosen grid spacing reduced pseudo land-use changes that could occur because of spatial accuracy problems (see 'Methodological annex' in Supplementary material). Nonetheless some implausible land-use changes occurred when intersecting the original datasets. Therefore, obvious classification errors were corrected for 1.57% of the area and an additional 0.58% was ignored.

2.4.2. Consideration of the various sources of uncertainties

Overlapping two different data sources produces a number of uncertainties, which cannot be fully disentangled and resolved. The following list presents the uncertainty types and options for addressing them:

- Thematic mismatch: diverging numbers of land-use categories or diverging definitions of land-use categories lead to a situation where a direct 1:1 translation between the land-use categories produces significant misclassification errors. We minimised them in this study by introducing a translation key that allowed a 1:n translation, which was calibrated to maximise spatial consistency.
- Temporal mismatch: overlapping two data sources requires at least one common year of data (Vol. 1 Chapter 5, IPCC, 2006). In our case study, the closest match was the period 2005–2008. The uncertainty from imperfect timing cannot be unambiguously separated from the thematic mismatch.
- Spatial resolution and spatial corrections in time series: aggregation and spatial errors can assign an incorrect land use to a certain area. The spatial uncertainty was minimised by working with point samples rather than with polygons (see above).
- Differences in the implementation of definitions: even if the same legends and data sources are used over time, differences in the interpretation and implementation of objects as points, lines or areas can produce apparent LUC. These artefacts can be minimised by harmonisation *via* pre-processing. The interpretation error, however, is almost impossible to verify or correct. In our case study the implementation differences were restricted to small landscape structures, which were excluded from the analyses.

2.4.3. Testing the mismatch between land-use category classifications

Differences in land-use definitions between data sources and legends could produce LUC artefacts. We tested the consistency in definitions from CIR 2005 to DLM 2008. We chose DLM 2008 to best match CIR 2005 since the temporal accuracy of DLM 2008 was likely to comprise a few years for agricultural land. Additionally DLM 2008 was the first DLM containing the attribute 'wet soil', which was critical information for our study. Further details of the test are described and visualised in the 'Methodological annex' in Supplementary material.

We give examples below of classification uncertainties and thematic mismatches that arise when combing different land-use datasets. It is also possible that classification uncertainty and thematic mismatch simultaneously affect a sample point.

Thematic mismatch of land-use categories: CIR contains habitats such as tall herbaceous vegetation, which could best be directly translated into grasslands in the DLM legend. In practice, however, the tall herbaceous vegetation areas in CIR 2005 corresponded to four different DLM 2008 land-use classes, only 84.8% (420 ha) of which are grassland. Given that the two datasets are close in time, it seems obvious that there is a strong translation artefact rather than a real LUC. Tests for other CIR categories resulted in iterative changes of sample points between non-forest – forest – non-forest and *vice versa*, which were also implausible given that forests are long-term landscape structures and protected by law (*e.g.* 200 ha in 2000, but not in 1992 or 2005).

Classification uncertainty: the conversion of grassland to cropland has been prohibited in the nature park since 1990 (Gesetzblatt der DDR, 1990). The nature park staff regularly monitor enforcement and have prosecuted the few offenders, immediately reconverting the croplands to grassland. As a consequence of this enforcement, any land conversion from grassland to cropland in the study area can be qualified as an artefact of classification uncertainty (due to ley farming) or thematic mismatch.

These artefacts or thematic mismatches encompassed 39 ha between 1992 and 2000, 30 ha in the period 2000–2008 and 8 ha between 2008 and 2012 when using a direct translation of land-use classes from CIR to DLM (*e.g.* $\text{cropland}_{CIR} = \text{cropland}_{DLM}$)

The reasons for the observed artefacts were probably a combination of classification uncertainty and aggregation error due to the coarser resolution of the DLM or ley farming. The problem separating grassland and cropland seems common for several remote-sensing products (*e.g.* Büttner et al., 2004).

The test to directly translate CIR into DLM legends (Table S1 in 'Methodological annex' in Supplementary material) highlighted that the direct translation produced significant overestimates of LUC. The direct translation in the research area resulted in LUC of 3719 ha year^{-1} between 2005 and 2008, including a loss of 98% (119 ha) of shrubs.

2.4.4. The translation key

We introduced a 'translation key' between the CIR and DLM datasets that allowed correction of the calculated LUC for classification uncertainty and thematic mismatch. After applying the key to the CIR datasets, any LUC involving CIR data was no longer identified as a change between two absolutely defined land use (LU) classes, but rather as a change in fractions of LU classes. Any real LUC was detected by a change in the LUC fractions. The translation key was applied to the gridded LU data and thus allowed the detection of gross LUC in a spatially explicit way, but could not distinguish between the real and artefact LUC with their exact geo-referenced coordinates. In other words, the translation key said that, for example, out of 100 ha of spatially, explicitly detected LU change from grassland to forest, 10% were artefacts and 90% were real LUC. The translation key allowed the most detailed LU information available to be kept and transparently accounted for any uncertainty associated with data mismatch or aggregation of LU classes. The translation key was calibrated with CIR 2005 and DLM 2008 (see 'Methodological annex' in Supplementary material).

For the validation of the translation key we calculated LUC from CIR 1992 to CIR 2005 ('untranslated'), aggregated to a classification level as DLM, excluding the attribute 'wet' and the land-use class 'road infrastructure' (Table S1). The aggregation performed should not be confused with the term 'direct translation', as only equal CIR datasets were involved.

We compared these results with the change from CIR 1992 to DLM 2008 ('translated') and with the sum of the changes in two periods from CIR 1992 to DLM 2000 and from DLM 2000 to DLM 2008.

The LUC derived from all three calculation approaches should be similar within the intrinsic uncertainties, provided that DLM 2008 contained information that was representative of 2005 and that there was not too much additional LUC between CIR 2005 and DLM 2008.

2.4.5. LUC areas and rates

LUC areas are presented as mean annual change rates in the period between the dataset years (1992–2000–2008–2012) as hectares $year^{-1}$ and as the fractional change of the study area in% $year^{-1}$. All land-use change rates were calculated relative to the year of release of the dataset concerned. For example, DLM 2008 represented 2008 in the analysis of LUC. The uncertainty in the real timing of the information in the DLM could lead to a certain misallocation of LUC to the wrong period, but did not change the absolute amount of LUC in the entire 20-year time series.

Information on land-use intensity was limited to the CIR datasets (1992 and 2005). Changes in land-use intensity were estimated based on CIR only.

2.5. Groundwater table and land use

For the period 1993–2004, there is a mean groundwater table map that was derived using the water management model 'WBalMo Drömling' (WASY, 2004). The model does not account for the water management measures since 1990 in the Drömling nature park (Langheinrich et al., 2010), and does not include recent groundwater table data (2004–2012). We used the time series of dipwell data from 1993 to 2012 and the digital elevation model (DEM) to construct a consistent series of groundwater table maps. For details see 'Methodological annex' in Supplementary material.

The mean groundwater table map generated for 1993–2004 was validated against the 'WBalMo Drömling' model (WASY, 2004). It revealed only minor discrepancies related to local effects of active water management, such as weirs or ditches.

In order to attribute groundwater table changes to management effects, we had to rule out the natural effects of inter-annual imbalances in the climatic water balance. We selected three periods that were as close as possible to the studied LUC periods with a similar climatic water balance (Table 2). As a result, we calculated groundwater table maps for the periods P 93–98, P 97–05 and P 04–10. The spatial extent of the maps varied slightly according to the location of available dipwell data (see 'Methodological annex' in Supplementary material).

Finally, the maps of the three periods (P 93–98, P 97–05, P 04–10) were intersected with the respective land-use dataset. The resulting maps were used to test whether land-use changes coincided with changes in the groundwater table. For example, LUC areas of the period 2008–2012 were intersected with the groundwater maps of the earlier datasets (P 97–05).

As a final step, the groundwater maps for the periods P 93–98 and P 97–05 were subtracted from the P 04–10-groundwater map and intersected with land-use data to estimate the absolute change in groundwater table over the past 20 years.

For the most recent changes in land use, a map of the difference between P 97–05 and P 04–10 was used. Negative values represented a decrease in the groundwater table; positive values represented an increase. The highest error variance of the variograms of P 93–98, P 97–05 and P 04–10 was defined as the threshold for detectable change (±0.03 m).

In linked groundwater and land-use analyses, we focused on land-use classes with LUC > 10 ha to obtain representative results for the majority of the research area. This restricted the analysis to fully geo-referenced changes between cropland, grassland and some grassland sub-classes. We were most interested in recent changes and therefore focused on the DLM datasets.

For enhanced visualisation and to minimise overestimations and underestimations we discarded all grid points where the water table was within the lower or upper 5% of water table values.

2.6. Software

All spatial operations and queries were processed by *pgAdmin III PostgreSQL Tools Version 1.14.0*. (pgAdmin Development Team, 2011) The preparation of groundwater table maps was performed by *Surfer Version 9.11.947* (Golden Software Inc., 2009). *ArcGIS 10.1* (ESRI 2012) was used to visualise spatial data and boxplots were computed by *R Version 2.14.1* (R-Development Core-Team, 2013).

3. Results

3.1. Translation key

In the translation key, forest types of the CIR classification matched the forest category of the DLM dataset by more than 98% (Fig. 2). CIR grasslands matched DLM grassland well, although some mix-up with cropland was observed. In the CIR classes of grassland, $cropland_{DLM}$ occurred at up to 23.8%, but for $cropland_{CIR}$ $grassland_{DLM}$ occurred at 14%. We cannot rule out a temporal mismatch between CIR 2005 and DLM 2008 for some areas or land-use classes, so a fraction of the mixed land-use classes could have resulted from real land-use change. The proportion of mixed DLM categories (10% $year^{-1}$, 1239.7 ha $year^{-1}$, see Table S1), however, was much greater than the proportion of typical land-use changes, which rarely exceeded 1% $year^{-1}$ (see also results below).

The significant share of $settlement_{DLM}$ in the CIR classes 'lawn' and 'orchard meadow', as well as the $grassland_{DLM}$ in $settlement_{CIR}$, could be explained by different selection criteria. For example, in contrast to CIR, DLM included household gardens in the land-use class 'settlement', while the land-use class '$garden_{DLM}$' referred to horticultural areas larger than one hectare without nursery buildings (AdV, 2003). The land-use class '$other_{DLM}$' in Fig. 2 referred to class shares of less than 1%, which have been aggregated for display.

Table 2
Overview of time series for the creation of groundwater table maps. Area coverage (%): amount of the research area that is covered by groundwater maps.

Name	Period	Dataset	Water Balance (mm)	Variogram Length (m)	Area Coverage (%)
P 93–98	1993–1998	CIR 1992	−1	4500	95.4
P 97–05	1997–2005	DLM 2000	−15	5300	97.5
P 04	2004	CIR 2005	−2	5200	97.6
−10	−2010	DLM 2008			
		DLM 2012			

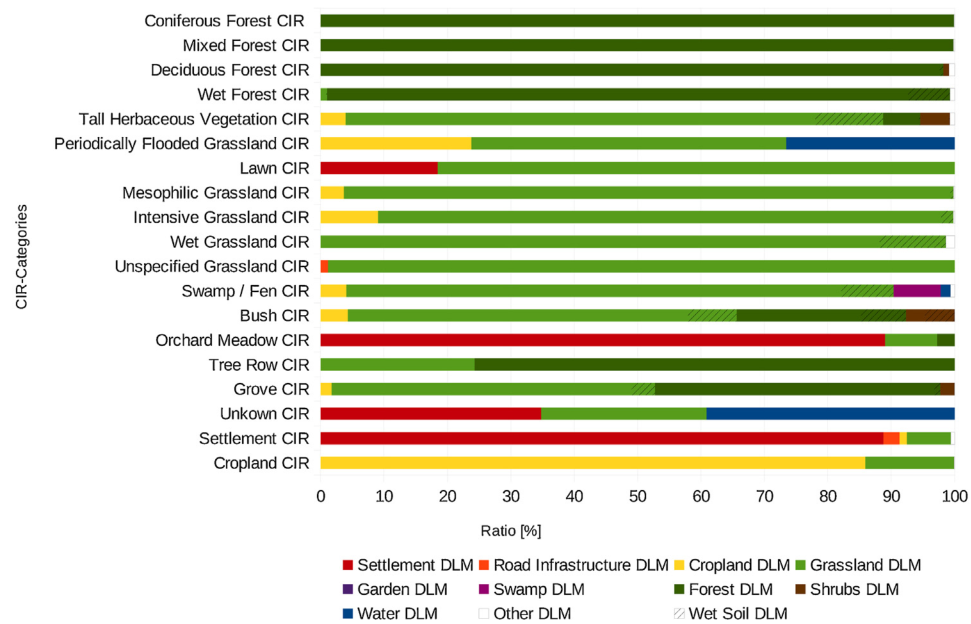

Fig. 2. Translation key: shows the shares of DLM land-use classes within each CIR land-use class.
On the x-axis all land-use classes of the CIR 2005 dataset are displayed. The y-axis displays ratios of the DLM 2008 dataset on the land-use classes of the CIR 2005 dataset. Each colour represents one land-use class of the DLM 2008 dataset, *e.g.* cropland in the CIR consists of 85.9% $Cropland_{DLM}$ and 14% $Grassland_{DLM}$ when there has been no land-use change.

The DLM attribute ‘wet soil’ was introduced as a new attribute in DLM 2008 and is yet not complete and consistent. We used it as secondary information. Wet soil occurred as a significant fraction of wet CIR-classes and in classes where a certain wet soil fraction could be expected (Fig. 2). Nevertheless, the wet CIR classes were more widely defined than the wet soil attribute.

For the analysis of land use, the fractional change from one unambiguously defined land use to another indicated LUC. The fractional change corrected the gross land-use changes for artefacts, but it was not possible to geo-reference the exact grid point where the change took place.

The application of the translation key determined a gross LUC of 42.9 ha $year^{-1}$ (0.35% $year^{-1}$ of the research area) from CIR 1992 to DLM 2008. LUC from CIR 1992 to CIR 2005 (aggregated) led to a gross LUC of 82.7 ha $year^{-1}$ (0.67% of the research area), which is nearly twice as high.

The summed LUC from 1992 to 2000 (0.25% year $^{-1}$; 31 ha year $^{-1}$) and from 2000 to 2008 (1.14% year $^{-1}$; 142 ha year $^{-1}$) resulted in an average LUC of 0.70% year $^{-1}$ (86.7 ha year $^{-1}$), which was comparable to the LUC from CIR 1992 to CIR 2005. The sum contained an unquantified amount of non-permanent land-use changes where the land use was re-converted to its original land use in 1992. The combined data suggested that the LUC rate was highest between 2000 and 2005.

Overall, the validation produced gross land-use changes in the same order of magnitude, but also highlighted a significant uncertainty of up to 50% in the annual LUC rates. The LUC rates were close to the German average LUC rate of 0.6% $year^{-1}$ (background data to the national inventory report (UBA, 2014).

3.2. *Major land uses and land-use intensity in 1992*

In 1992, more than two thirds of the Drömling nature park was used as grassland, while the remainder was mainly used as cropland and forest (Table 3).

In 1992, the intensity of the grassland use was medium, with frequent occurrences of mesophilic grassland (3507 ha, 28% of the nature park area), high-intensity grassland (2644 ha, 21%) and wet grassland (2278 ha, 18%).

Major forest types were deciduous (699 ha, 6%) and wet forests (392 ha 3%). Mixed and coniferous forests occurred in less than 0.5% of the nature park. Tall herbaceous vegetation covered 2.6% (306 ha). All other land uses occurred on less than 1% of the area.

Table 3
Distribution of land-use classes (%) in the mapping years.

	1992	2000	2008	2012
Settlement	0.26	0.18	0.18	0.17
Road Infrastructure	0.01	0.00	0.01	0.01
Cropland	19.22	18.56	15.49	15.63
Grassland	70.46	71.41	73.49	73.17
Garden	0.00	0.00	0.00	0.01
Swamp	0.00	0.00	0.33	0.44
Forest	9.81	9.79	10.38	10.36
Shrubs	0.20	0.01	0.33	0.44
Unknown	0.05	0.03	0.00	0.00
Water	0.04	0.02	0.10	0.16

3.3. *Land-use change from 1992 to 2012*

Land-use changes were analysed for the periods 1992–2000 (eight years), 2000–2008 (eight years) and 2008–2012 (four years).

3.3.1. *Gross land-use change*

3.3.1.1. 1992–2000. To differentiate between CIR and DLM data, land-use classes in this sub-section were subscripted with $_{CIR}$ or $_{DLM}$.

Overall, a gross land-use change of 31.33 ha $year^{-1}$ was detected (Table 4). This corresponded to a change of 0.25% $year^{-1}$ in the research area.

A land-use change matrix (Table 5) illustrates the change of land-use classes from 1992 (CIR dataset) to 2000 (DLM dataset). The percentages represent the LUC after applying the translation key. Blue values refer to a gain and red values refer to a loss. The land-use class ‘$other_{CIR}$’ refers to land-use classes that were not

Table 4
Relative and absolute gross land-use change within the analysed time series.

Time Series	Change in Time Series (%)	Change/Year (%)	Absolute Change/Year (ha)
1992–2000	2.02	0.25	31.3
2000–2008	9.15	1.14	142.0
2008–2012	2.05	0.51	63.64

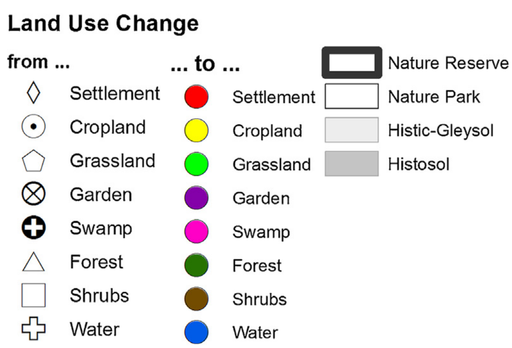

Fig. 3. Legend to Figs. 4 and 5.
The shape of the symbol represents the land-use class before changes occur, whereas the colour of the symbol represents the land-use class after the land use has changed.

implemented in the translation key or did not occur in 1992. Those classes were not included in the LUC calculation.

LUC between 1992 and 2000 was characterised by reduced intensity and spatial re-organisation. About 105 ha (13.16 ha year^{-1}) of cropland$_{CIR}$ were converted to grassland$_{DLM}$. Cropland$_{CIR}$ lost the largest absolute share (13.4 ha year^{-1}) of all major land-use classes. This corresponded to a change of 0.85% year^{-1} of the research area. Furthermore, wet grassland$_{CIR}$ and high-intensity grassland$_{CIR}$ made a major contribution to the total LUC (4.4 ha year^{-1} and 4.9 ha year^{-1} respectively). The LUC was dominated by spatial shifts between the two grassland types. The largest relative changes per class occurred in small land-use classes, such as orchard meadow$_{CIR}$ (44% year^{-1}, 0.06 ha year^{-1}). Their occurrence in DLM datasets could vary strongly, but they had nearly no effect on the total gross land-use change in Drömling.

3.3.1.2. 2000–2008 (DLM data only). The greatest land-use change in the past 20 years occurred between 2000 and 2008 (Table 4 and Fig. 4), intensifying previous trends. Between 2000 and 2008, gross LUC occurred on 1136 ha or 9% of the study area (1.14% year^{-1}, 142 ha year^{-1}). During this period predominantly croplands were converted to grassland (81.07 ha year^{-1}). Furthermore, remarkably large areas of grassland and cropland, mainly within the nature reserve, were converted to forest (12.76 ha year^{-1}) or shrubs (4.55 ha year^{-1}). In contrast to this development, grassland was converted to cropland (37.31 ha year^{-1}), mainly in marginal areas of the nature reserve and on fringes of organic soils (Figs. 3 and 4). The gain in swamp areas (0.43 ha year^{-1}) and water bodies (1.3 ha year^{-1}) was higher than the loss (0.02 ha year^{-1} in both cases).

3.3.1.3. 2008–2012 (DLM data only). During the period 2008–2012 (Figs. 3 and 5), LUC rates decreased compared to the previous period (Table 4). Gross LUC occurred on 255 ha (0.51% year^{-1} of the study area, 63.4 ha year^{-1}). The most important change during this period was a conversion from grassland to cropland (22 ha year^{-1}), which was in contrast to the trend of the previous periods. Again, the resulting new croplands were mostly located on the edge of the nature reserve. The change from cropland to grassland comprised 16.29 ha year^{-1}. Another striking change was the conversion from wet grassland to grassland (11.25 ha year^{-1}). The change from grassland to wet grassland was much smaller (3.55 ha year^{-1}). Further changes occurred from grassland to forest (2.21 ha year^{-1}) and *vice versa* (1.14 ha year^{-1}), as well as from grassland to water bodies (1.82 ha year^{-1}) and from forest to shrubs (1.56 ha year^{-1}) (Figs. 3 and 5).

When comparing Figs. 4 and 5, it is important to bear in mind that Fig. 4 displays eight years of land-use change, while Fig. 5 shows only four years.

3.3.1.4. Change in land-use intensity. The grassland intensity mix changed from 1992 to 2005 (CIR data only) to both high-intensity and wet grassland, with a loss of mesophilic grassland. Wet forests increased to 4% of the study area (538 ha) at the expense of mixed and deciduous forest types. Tall herbaceous vegetation (306 ha, 2.6% in 1992) increased by 60% (495 ha, 4% in 2005). The changes in finer thematic intensity available in the CIR datasets confirmed the trends towards reduced land-use intensity and re-organisation detected in the more aggregated analysis with DLM above.

3.3.2. Net land-use change

For net land-use change only DLM categories were valid. CIR 1992 was translated to DLM before an analysis of land use changes.

Table 5
Matrix for detection of land-use change between the CIR 1992 and the DLM 2000 datasets after application of the translation key. Blue = gain of the land-use class in hectares; red = loss of the land-use class in hectares. (For interpretation of the references to color in this table, the reader is referred to the web version of this article.).

Change in hectares	DLM 2000											
CIR 1992	Settlement $_{DLM}$	Road Infrastructure $_{DLM}$	Cropland $_{DLM}$	Grassland $_{DLM}$	Garden $_{DLM}$	Swamp $_{DLM}$	Forest $_{DLM}$	Shrubs $_{DLM}$	Unknown $_{DLM}$	Water $_{DLM}$	Area [ha]	Land use change per class [%]
Cropland $_{CIR}$	0.0	0.2	-104.6	104.4	0.1		0.4	0.0	0.2	-0.6	**2329.7**	4.5
Settlement $_{CIR}$	-7.2	-0.7	0.4	7.7			-0.1			0.0	**29.5**	27.3
Unknown $_{CIR}$	-4.8		0.8	7.5			0.6		1.2	-5.4	**13.8**	73.9
Grove $_{CIR}$	0.0		2.7	-1.8			-0.2	-0.8		0.0	**48.7**	5.7
Orchard Meadow $_{CIR}$	-0.5		0.1	0.4	0.0		0.0				**1.2**	44.0
Bush $_{CIR}$	0.0		0.9	9.6			-7.1	-3.4			**44.9**	23.4
Swamp / Fen $_{CIR}$			-0.1	0.1		-0.3	0.4			-0.1	**6.8**	7.4
Unspecified Grassland $_{CIR}$		0.0	1.2	-1.2							**1.2**	99.2
Wet Grassland $_{CIR}$	0.1		24.8	-26.6		-0.1	10.3	-7.1	0.3	-1.6	**2278.1**	1.6
Intensive Grassland $_{CIR}$	-0.2		-35.1	38.6	0.0		-2.0	-0.1	0.2	-1.5	**2644.6**	1.5
Mesophilic Grassland $_{CIR}$	-0.4		11.7	-10.0	0.0		-0.6	-0.1		-0.6	**3507.4**	0.3
Wet Forest $_{CIR}$				0.9							**0.9**	0.0
Deciduous Forest $_{CIR}$	0.2		4.6	9.7			-0.8	-13.9	2.1	-1.9	**306.3**	5.4
Mixed Forest $_{CIR}$			-0.1	1.8		-2.1	0.7	-0.2	0.1	-0.2	**393.0**	0.6
Coniferous Forest $_{CIR}$			0.7	4.1			1.2	-5.6		-0.4	**699.1**	0.9
Other $_{CIR}$											**60.2**	

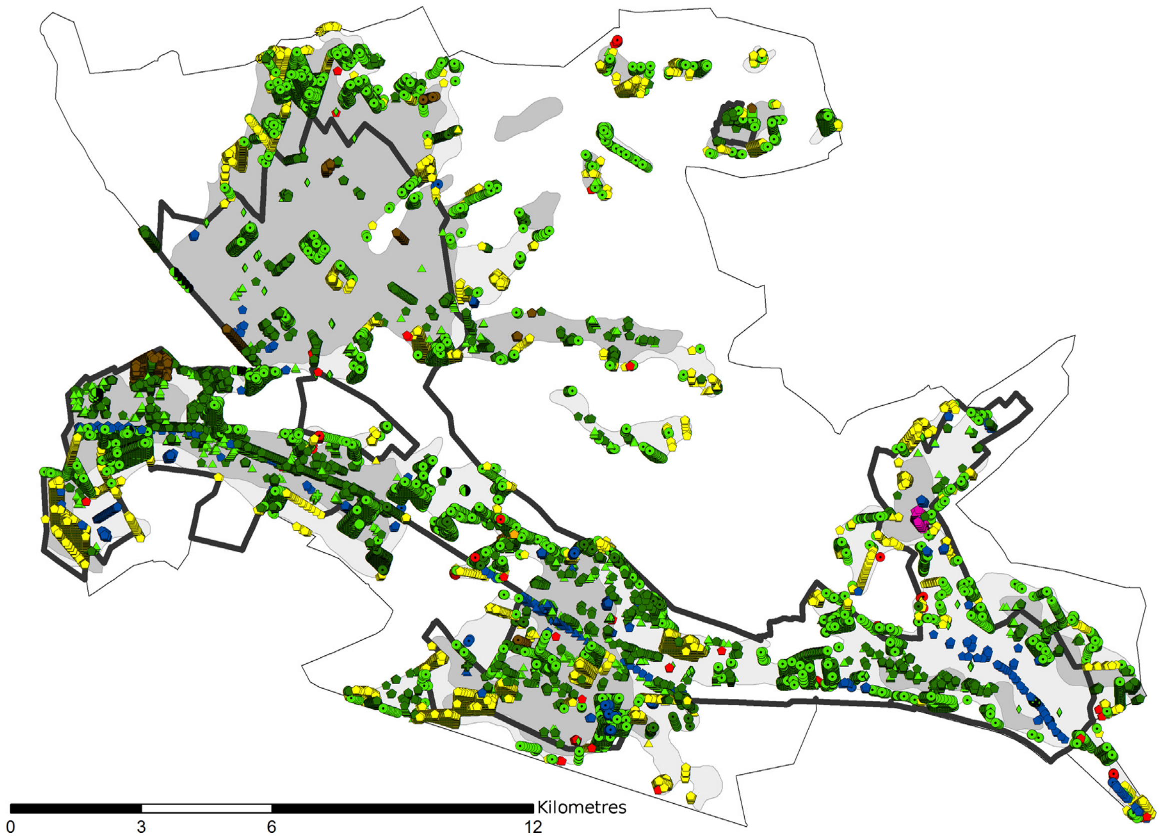

Fig. 4. Spatially explicit gross land-use change from 2000 to 2008.

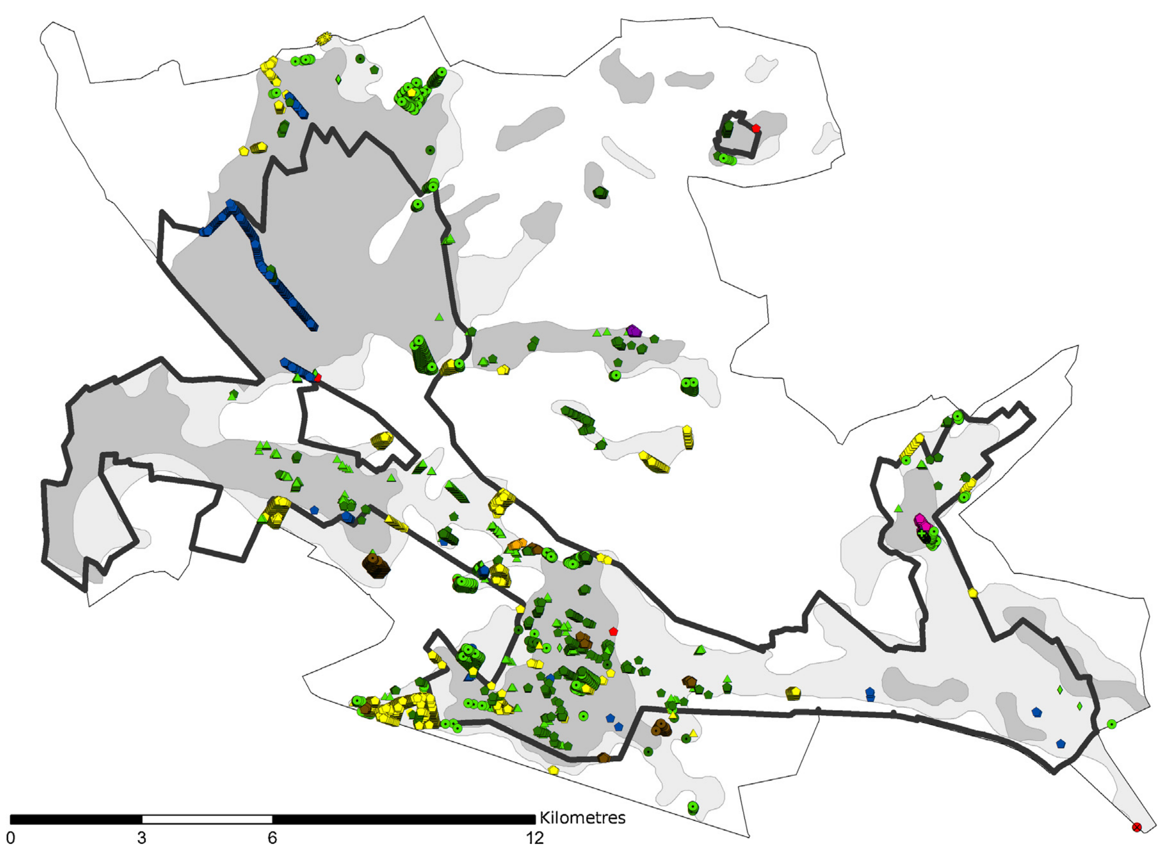

Fig. 5. Spatially explicit gross land-use change from 2008 to 2012.

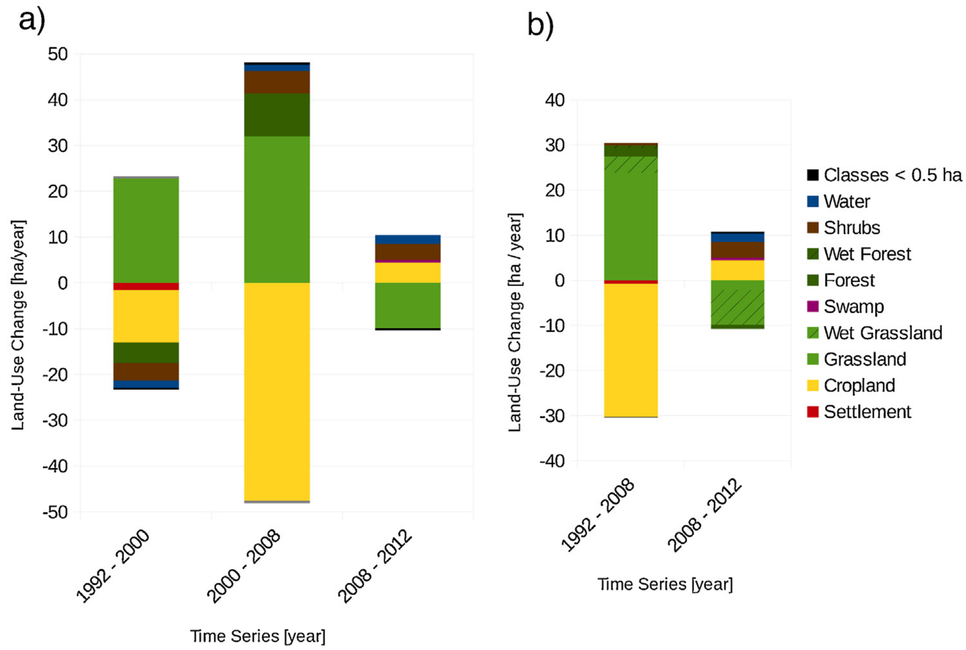

Fig. 6. Net land-use change per year in different time series a) without and b) with the attribute 'wet soil'. The year 2000 cannot be used for b) because no information on 'wet soil' is available.

From 1992 to 2000, the grassland area grew, while cropland, forest, shrubs and even water bodies decreased. From 2000 to 2008 swamps, water bodies, shrubs and forest started to increase at the expense of cropland. Between 2008 and 2012 cropland gained in area while grassland reduced.

In total from 1992 to 2008, the cropland area decreased, while grasslands increased (Fig. 6a).

Taking into account the additional intensity information 'wet soil' of DLM 2008 and 2012, the size of wet grassland and wet forest increased from 1992 to 2008, but decreased again in the period from 2008 to 2012 (Fig. 6b).

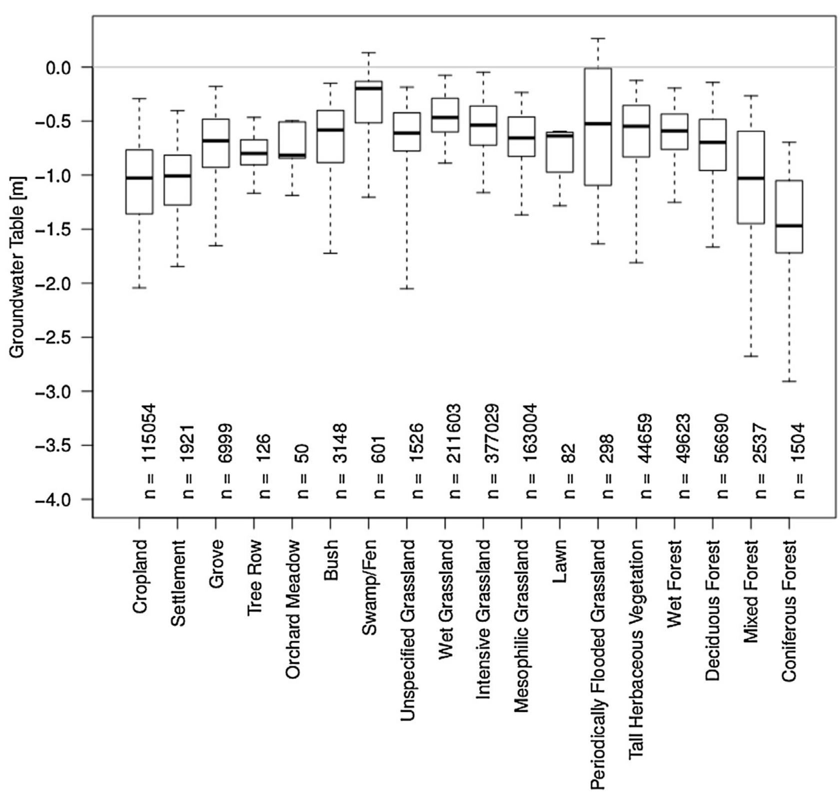

Fig. 7. Groundwater table per land-use class (confidence interval: 90%) of CIR 2005 in P 04–10 (n = 1 ≙ 0.01 ha). Black line: median, box: inter-quartile range, dashed line: 90% range, outliers excluded.

3.3.3. Gross versus net land-use change

The ratio of gross to net land-use change characterises land-use dynamics. A ratio close to one indicates there is a trend towards specific types of LU in the observed changes. A ratio close to zero indicates that LU is reorganised spatially, but largely remains the same when summed over the study area.

The highest ratio (74.3%; 23.3 ha $year^{-1}$ *vs.* 31.3 ha $year^{-1}$) of gross to net change occurred in the period 1992–2000. This implied a trend towards specific types of land use and could be explained by the extending trend of grassland. The second period (2000–2008) showed the highest gross and net land-use change (Table 4 and Fig. 6), but the share (33.9%; 48.1 ha $year^{-1}$ *vs.* 142.0 ha $year^{-1}$) of net change to gross change was only half as great as in the first period. The centre and fringes of the organic soils showed a contrasting trend in this period (Fig. 4). Only one third of the gross land-use change was a net change of land use, with predominant changes from cropland to grassland, forestry or shrubs. During the last period, the share of net change to gross change was further reduced to 16.6%. Out of a gross land-use change of 63.6 ha per year, only 10.6 ha constituted a net land-use change.

3.4. Groundwater table and land use

3.4.1. Groundwater map 1993–2004

The groundwater table map of the groundwater model and the new interpolated map agreed with a mean offset of 0.0 m and a standard deviation of 0.17 m. We accepted the interpolated maps for further analysis. The highest uncertainties of the maps were located on fringe areas where both the difference between the new groundwater map and the groundwater model and the Kriging cross-validation errors (P 93–98: 0.82 m, P 97–05: 0.79 m, P 04–10: 0.84 m) were highest.

3.4.2. Groundwater maps and land use

The maps P 93–98 (1993–1998), P 97–05 (1997–2005), P 04–10 (2004–2010) were intersected with the corresponding land-use dataset(s). All land-use maps (CIR 1992, DLM 2000, DLM 2008 and DLM 2012 (including ‘wet soil’)) displayed plausible groundwater

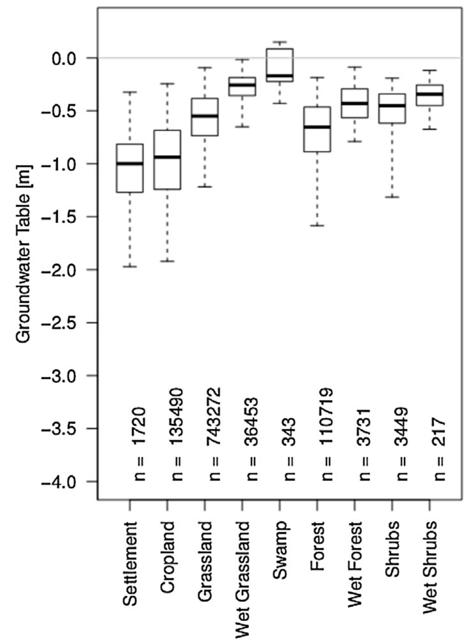

Fig. 8. Groundwater table per land-use class (confidence interval: 90%) of DLM 2008 in P 04–10 (n = 1 ≙ 0.01 ha).
Black line: median, box: inter-quartile range, dashed line: 90% range, outliers excluded.

tables for similar land-use classes (Figs. 7 and 8). Generally, the uncertainty was highest for low groundwater tables.

Land-use classes with the attribute ‘wet soil’ showed a higher groundwater table than the same land-use classes without this attribute (Fig. 8).

3.4.3. Groundwater table *vs.* land-use change

Generally, all groundwater tables met expectations. We found only a slight difference between the groundwater table of cropland remaining cropland and cropland changing to grassland (Fig. 9a).

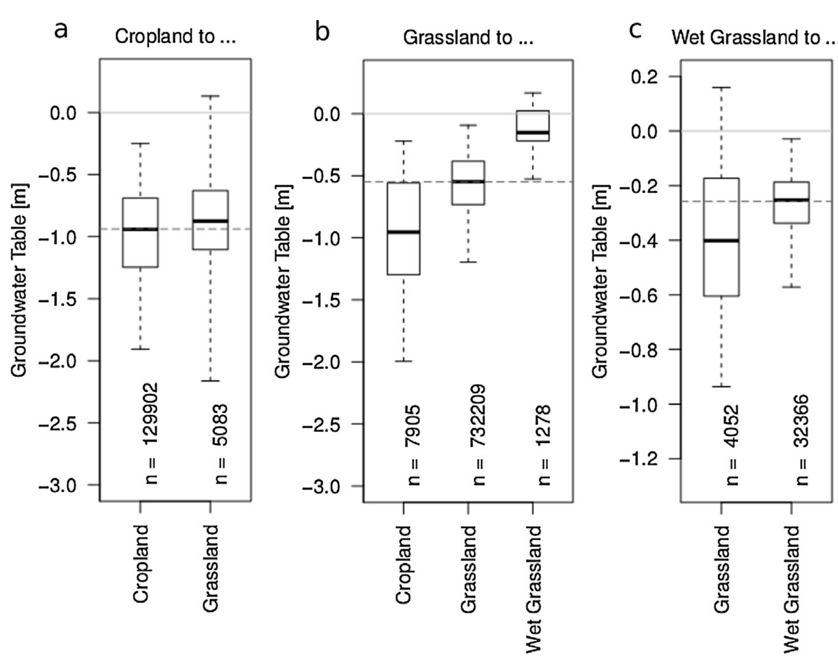

Fig. 9. Groundwater table (confidence interval: 90%) of cropland (a), grassland (b) and wet grassland (c) in 2008 plotted as the land-use classes of 2012 (only areas > 10 ha, n = 1 ≙ 0.01 ha).
Black line: median, box: inter-quartile range, dashed line: 90% range, outliers excluded. The solid grey line refers to land surface, the dashed grey line displays the median of the land-use class in 2008.

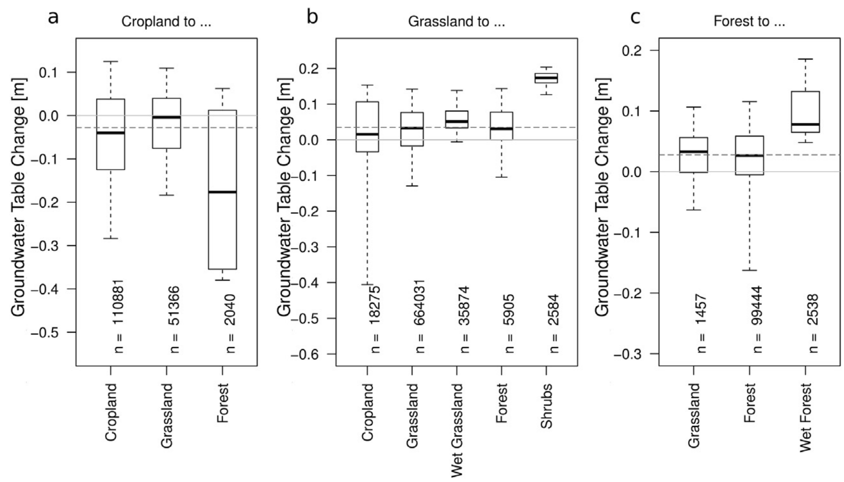

Fig. 10. Change in groundwater table (P 04–10–P 93–98) (confidence interval: 90%) of cropland (a), grassland (b) and forest (c) in 2000 plotted as the land-use classes of 2008 (only land-use classes > 10 ha, n = 1 ≙ 0.01 ha). Black line: median, box: inter-quartile range, dashed line: 90% range, outliers excluded. The solid grey line refers to no change in the groundwater table; the dashed grey line displays the median of the land-use class of 2000.

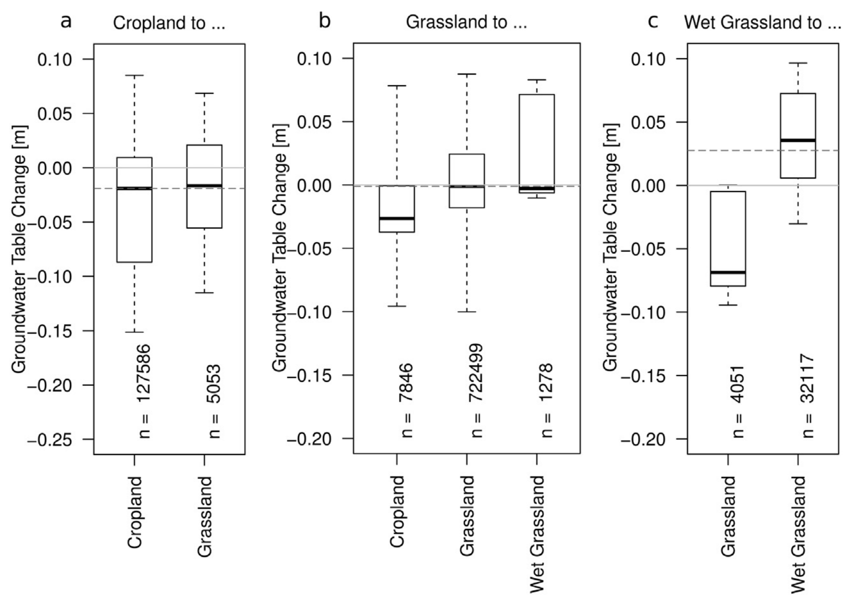

Fig. 11. Change in groundwater table (P 04–10–P 97–05) (confidence interval: 90%) of cropland (a), grassland (b) and wet grassland (c) in 2008 plotted as the land-use classes of 2012 (only land-use classes > 10 ha, n = 1 ≙ 0.01 ha).
Black line: median, box: inter-quartile range, dashed line: 90% range, outliers excluded. The solid grey line refers to no change in the groundwater table; the dashed grey line displays the median of the land-use class of 2008.

However, the 'new' grassland was considerably drier than the grassland that remained grassland (Fig. 9b). Grassland changing to cropland had a similar groundwater table as the cropland of 2008 and thus LUC occurred in areas with a comparatively low groundwater table.

Fig. 9b clearly shows that the areas changing from grassland to wet grassland already had a much higher groundwater table before they were actually converted to wet grassland and *vice versa* (Fig. 9c).

3.4.4. *Changing groundwater table* vs. *land-use change*

3.4.4.1. P 93–98 minus P 04–10. While the groundwater table rose by up to 25 cm in most (49%) of the organic soils, it fell by up to 42 cm in 25% of the study area, mainly in the south-western part. No change took place in 26% of the area. Two centres of changes towards a higher groundwater table were located in the north-western and south-eastern parts of the Drömling nature park, where there are the largest areas of organic soils. The largest fall in the groundwater table took place at marginal sites without dip-wells and thus with a higher uncertainty. With respect to changes in groundwater table for the total period (P 93–98 to P 04–10), those grid points that changed land use showed that croplands tended to become drier, while grasslands and forests became slightly wetter (Fig. 10). Cropland areas that changed to grassland almost retained the same groundwater table (Fig. 10a). Areas changing from grassland to any other land-use class (>10 ha) between 2000 and 2008 mainly underwent a rise in the groundwater table (positive values). Areas converted to cropland in this period changed least. Between 2000 and 2008 shrubs changed by more than 10 centimetres (Fig. 10b). Forest areas that changed to grassland or wet forest or that remained as forest during 2000 and 2008 mainly showed a rise in the groundwater table, with wet forest experiencing the greatest change (Fig. 10c).

3.4.4.2. P 97–05 minus P 04–10. From P 97–05 to P 04–10, the groundwater table in more than half of the research area remained unchanged (56%). The groundwater table rose by up to 0.33 m in the western and north-eastern part of the study area (23%). A reduction in the groundwater table of up to 0.48 m from P 97–05 to P 04–10 was observed in 21% of the research area. The largest fall was located in the north-western and south-western areas and, again, on the most uncertain fringes of both groundwater maps. Cropland areas (Fig. 11a) became only marginally drier (median of about 2 cm), irrespective of whether they changed to grassland or remained as cropland from 2008 to 2012.

Grassland areas remaining as grassland or converted to wet grassland did not show clear changes in groundwater table (WT). Grassland converted to cropland experienced a fall in the groundwater table (Fig. 11b). Wet grassland that remained wet grassland became wetter, while 95% of wet grassland changing to grassland showed a fall in the groundwater table during P 97–05 and P 04–10 (Fig. 11c).

Overall, a greater segregation of the landscape occurred over the whole study period: while the centre of the nature park became wetter and dominated by grassland and more natural vegetation types, the fringes were used more intensively and also tended to become drier.

4. Discussion

4.1. Data quality

There were obvious temporal inconsistencies in the land-use products. The very time-consuming corrections of obvious inconsistencies affected only 2.15% of the area and had a negligible effect on the LUC assessment.

High LUC rates in both directions between different land-use classes gave an initial indication of potential inconsistencies in classification, but a robust indication required spatially explicit LUC data.

The amount of cropland and grassland could also produce a high LUC rate, as the differentiation between these two land-use classes is often difficult and thus can lead to misclassification (Büttner et al., 2004).

Furthermore some changes appeared to be very high in detailed land-use information such as intensity. This could have resulted from changes or inconsistencies in the interpretation methodology in raw data processing. For example alder trees could be classified either as deciduous forest or as wet forest because this species prefers wet locations (Ellenberg et al., 1992). It can also be difficult to differentiate between grassland types just by aerial photos (LAU, 1999).

4.2. The translation key

The translation key required two datasets from the same year for calibration. In our study we used DLM 2008 to best match CIR 2005 because of its unclear temporal accuracy ('Methodological annex' in Supplementary material). The unclear acquisition date of the DLM dataset created an unknown uncertainty in the translation key. We cannot rule out that some fraction of the mismatches found were real land-use changes.

If datasets for the same time period are available, the translation key offers an opportunity to overlap land-use datasets with diverging spatial resolution and thematic content. The translation key can be recommended as a splicing technique (IPCC, 2006, Vol 1 Chapter 5) to reconstruct consistent time series of land use and gross land-use change irrespective of the spatial or thematic resolution and without loss of information.

Furthermore, the translation key transparently showed how the original datasets were converted. It avoided any additional post-processing that is typically necessary to correct the estimated land-use changes from directly translated data sources to land-use trends detected by repeated forest inventories or agricultural statistics (*e.g.* UBA, 2014). Such post-processing is typically vaguely described as validation or verification (*e.g.* IPCC, 2006, Vol. 4 Chapter 3) and applies similar procedures as the translation key and also results in non-geo-referenced, spatially explicit gross land-use changes.

Calculation of LUC by different datasets with a direct translation (*e.g.* herbaceous vegetation = grassland) always implies a certain degree of expert judgment about the likely best match between land-use categories in different data sources. The direct translation would result in a massive overestimation of LUC (see 'Methodological annex' in Supplementary material). In our case study we produced a translation key using two datasets of different spatial and thematic resolution. Our method is applicable to other regions, larger scales and different issues if appropriate datasets are available.

LUC cannot be located to the exact grid point when applying the translation key, therefore it is impossible to distinguish between permanent (*e.g.* change from grassland to forest) and non-permanent land-use change (*e.g.* change from cropland to fallow land to cropland).

4.3. Land-use change trends

The large share of net to gross land-use change (74.4%) in the first period (1992–2000) was in agreement with the conservation and water management measures that began in 1990. Among other things, these measures were targeting the conversion of cropland to grassland with small structures such as hedges. The predominant land-use changes during the second period from cropland to grassland, forest or shrubs were again in agreement with the aims of reducing land-use intensity (Benecke, 1993), although the major part of the gross land-use change corresponded to spatial shifts in land use (Section 3.3.3). This was consistent with the zonal concept of protected core areas and a more intensively used buffer zone. During the last period, opposing trends were detected. In some parts of the research area no change took place, such as in the south-western part of the nature reserve. This is in agreement with the highest protection level, including the ban on using and entering the area since 1990 (Müller and Braumann, 1993).

Groundwater table changes matched the zonal concept. Management decisions were obviously taken according to spatial planning and zonal targets rather than being driven by site limitations, such as unsuccessful cropping on wet soils. Our independent monitoring showed that the zonal concept has been successfully implemented.

Besides spatial shifts, non-permanent LUC, in particular ley grassland lasting for several years in a crop rotation, could explain some of the difference in gross and net land-use change, particularly on the dry fringes of the study area. Without additional management information and precise time stamps it was not possible to quantify permanent and non-permanent land-use change for the DLM datasets used.

Overall, most land-use changes occurred before 2008. Trends in the Drömling nature park are in contrast with trends in national land-use changes (Nitsch et al., 2012; UBA, 2014). The gain in grassland and the loss of cropland highlight the success of the conservation measures, but that some part of this pattern results from ley farming cannot be ruled out. Between 1990 and 2006 the area of permanent grassland declined in Germany. This trend has intensified since 2005, even on organic soils (UBA, 2014), although agrarian reform in Germany has tried to prevent further loss of

Table 6
Allocation of the organic soil area in the Drömling nature park to the Kyoto activities in 2012.

Kyoto activity	Area in 2012 (ha)	Comments
Afforestation/reforestation (AR)	95.4	Land converted to forest since 1990
Deforestation (D)	22.1	Land converted from forest to any other land use since 1990
Forest management (FM)	1176.3	All forest not included in AR and D
Cropland management (CM)	1948.3	All land under cropland in 2012
Grazing land management (GM)	9132.8	All land under grassland in 2012
Wetland drainage and rewetting (WDR)	4.8	Land not included in any other activity on which the groundwater level has changed compared to 1990
Land not accounted in any activity	38.8	

grassland (Nitsch et al., 2012). An increasing trend of grasslands being converted to cropland in the research area can nonetheless be excluded. The conversion of any land use to cropland is prohibited and has been illegal in the nature park since 1990 (Gesetzblatt der DDR, 1990). The reason for the results of land converted to cropland within the last period can mainly be attributed to ley farming and misclassifications in the datasets. Ley farming is a common practice in the nature park, resulting in grassland-like areas that have to be ploughed at least once every five years. Furthermore the problem of separating grassland and cropland seems common for several remote-sensing products (*e.g.* Büttner et al., 2004). This assumption is further supported by the fact that changes from 'grassland' to 'cropland' occurred only in the shortest period from 2008 to 2012. The shorter the period, the more likely it is for rare changes to be detected. Over longer periods it is more likely that those changes occurred between the recording times rather than slightly before the recording. In conclusion, parts of the grassland areas in the nature park have a 'cropland status', but it is not possible to distinguish between grassland-like croplands and permanent grasslands with the data used in this study. Long-term annual datasets with a high temporal accuracy or detailed information of farmers would be required to resolve this issue.

4.4. *Groundwater table* vs. *land use*

There was a moderately strong relationship between land use and the groundwater table (Figs. 7 and 8), but all the results were plausible and met expectations. Even the relatively coarse-grained dataset 'DLM' represented plausible median values. The high scatter within the individual land-use classes could be explained by both the simplified derivation of the groundwater map and the expected variability in groundwater tables within one land-use class. Further reasons for the uncertainty in the groundwater maps were a lack of information about weirs, blocked ditches and tile drains.

Our analysis showed the usefulness of the 'wet soil' DLM attribute for land-use intensity. Indeed, not all land-use classes without this attribute are actually dry, but areas will definitely be wet if this attribute is present. Therefore, the attribute is robust, but not necessarily complete in terms of covering all moist and wet species. Any new occurrence of the attribute indicates a transition to a really wet status. Information on the attribute 'wet soil' could be even more useful if it were combined with a groundwater table map such as the one available for the Drömling nature park or for organic soils in general (Bechtold et al., 2014). Quantitative information on levels of rewetting and drainage, however, can only be based on groundwater table data.

4.5. *Implications for Kyoto activity monitoring*

Germany accounts for afforestation/reforestation (AR) and deforestation (D), forest management (FM), cropland management (CM), and grazing land management (GM) in the second Kyoto commitment period, but not for wetland drainage and rewetting (WDR). All activities include GHG emissions from organic soils under the respective accounting rules. We do not have data for 2013, the start year of accounting, but can show the allocation of the organic soil area to the Kyoto activities in 2012 (Table 6) according to the German definition of the land under these Kyoto activities. The largest area is allocated to GM. As WDR is hierarchically last, it would only occupy a negligible area.

The Kyoto activities CM, GM and WDR are accounted for against the base year 1990. Uncertainty in the base year GHG emissions has been highlighted as presenting a major challenge (Weiss et al., 2015). In our case study, the detailed land-use classification of 1992 combined with the interpolated water table map constituted a robust base year reference. Land-use categories and water table data were derived using consistent methodologies as consistent time series for the 20-year period until 2012. These data will also be available in future. The land-use classification is far more detailed than the land-use categories on which the IPCC default emission factors are based. It stratifies major land-use categories by management and drainage status, which allows GHG reporting and accounting with detailed, so-called 'higher tier' methodologies. The German national GHG inventory estimates GHG emissions from drained organic soils by a response function of GHGs to mean annual groundwater table (UBA, 2015; Chapter 6.1.2.2). So far, however, a time series of changes in mean annual groundwater table is not available on a national level. Detailed LU sub-categories and changes therein, as demonstrated in the case study, could serve as activity data proxies for reporting and monitoring. Such detailed methodologies are mandatory if countries wish to account for management and drainage and rewetting practices. Water table information is the most critical information for WDR accounting and for accounting for drainage and rewetting practices in other activities under the Kyoto Protocol. For accounting purposes under the Kyoto Protocol, remotely sensed land-use datasets should be cross-checked against groundwater data.

5. Conclusions

We developed a 'translation key' to combine land-use datasets from heterogeneous sources and with heterogeneous spatial and thematic resolution. It successfully generated a consistent time series of land use and land-use change over a 20-year period. The time series not only allowed land use to be tracked, but also land-use intensity by detailed land-use subcategories of grasslands, forests and others as a proxy for soil wetness. This is a prerequisite for accounting for the elective land use-based activities under the Kyoto Protocol (cropland management (CM), grazing land management (GM) and wetland drainage and rewetting (WDR)). The methodology is generally applicable elsewhere and also relevant for mineral soils if land-use datasets from a similar time period are available for calibration.

We have demonstrated that land-use changes, nature conservation measures and groundwater table changes in organic soils in the Drömling nature park can be tracked. Our study indicates that detailed land-use time series can serve as a semi-quantitative proxy for groundwater depth, but any robust quantitative assessment of water table changes requires *in situ* data, *e.g.* from a network of dipwells. The combination of land-use and dipwell data provide a very accurate basis for estimating GHG emission from organic soils, which is the core of the Kyoto activity WDR, but also part of afforestation/reforestation (AR) and deforestation (D), forest management (FM), CM and GM. Even the detailed land-use time series alone would fulfil the requirements for WDR accounting, yet with considerable uncertainty about the drainage status of the organic soils.

The proposed approach is not limited to calculating GHG emissions from organic soils. Any kind of monitoring, be it biodiversity, agricultural policy *etc.*, requires consistent time series against a pre-measured status. Problems with inconsistent datasets in the past will also continue to emerge in future, simply because of ongoing progress in monitoring technologies and implementation.

The highly detailed CIR data were originally generated for monitoring vegetation types and habitat types. They contain a lot of detailed information, in particular on grassland types and vegetation attributes that can be interpreted as wetness indicators. This kind of land-use data used for monitoring under the Flora-Fauna-Habitats Directive of the European Commission are available in many regions and have strong synergies with the data needs for reporting on and accounting for land-use activities under the Kyoto Protocol.

Detailed time series, such as those in our study region, would also allow more sophisticated GHG estimates based on functional relationships between land use, water tables and GHG emissions.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.landusepol.2016.04.016.

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Supplementary material: Methodological annex

Correcting the spatial representation bias: the grid sample approach

Our land-use time series used non-ideal data sources, which differed in spatial and thematic resolution. Depending on the data source, land-use classes may be displayed as polygons, lines or points. These differences occurred both between CIR and DLM and within each time series as the implementation of small objects may have changed. For example, different people in charge implemented most tree rows in CIR 1992 as areas (polygon) and in CIR 2005 as lines) [LAU, 1999]. Due to these differences in the datasets, a simple intersection of the original polygons was inappropriate for detecting land-use changes.

The grid sample approach intersects all spatial data sets with a systematic grid. Therefore, we only worked with point data. This approach minimised artefacts induced by time-series inconsistencies and differences in spatial resolution as the grid points sampled the polygon areas representatively, but it is less susceptible to uncertainties in the location of edges and very small polygons [*e.g.* UBA, 2014]. The edges of the polygons are uncertain when the spatial resolution of maps differs, when the representation of small objects varies or when minor updates of the maps shift the boundary of a polygon due to a geometrical correction rather than due to LUC. As a consequence, small polygons typically emerge as artefacts when intersecting heterogeneous land-use map time series. Correcting these inconsistencies manually would be extremely time consuming and arbitrary. Grid sampling has turned out to be robust for the analysis of LUC based on maps of heterogeneous origin. We used a statistical point sample approach, not a spatial raster grid approach that would assign the dominant land use to a grid cell. Mathematically, the result would be the same if the land use in the centre of the cell is identical to the major land use in the grid cell. In terms of the accuracy of LUC detection in a time series, the statistical point sample avoided artefacts of marginal LUC due to small fractional changes in mixed grid cells or of spatial aggregation or spatial corrections of polygons. This approach is a transparent and commonly applied solution for generating consistent time series of LUC from datasets with minor geometrical inconsistencies [IPCC, 2006].

Choosing the data sets with the best thematic and temporal match

To compare CIR and DLM datasets, we needed both datasets representing the same year. The CIR data set was recorded from June to September 2005. Land uses other than settlements and infrastructure were recorded in DLM 2008 with time stamps mainly between 2005 and 2008. Settlements and infrastructure mainly reflected 2008. This was the best available temporal match with CIR 2005. Another reason for choosing the DLM 2008 was the ‘wet soil’ attribute that was first recorded in DLM 2008. Considering that DLM 2008 contains a mix of time stamps rather than the exact situation in any year, this dataset was the best of all uncertain options. It includes as much information as possible and matched the situation in CIR 2005 as closely as possible. It cannot be ruled out, however, that some LUC may be missed or misallocated due to the temporal gap between the two datasets.

Correcting the thematic representation bias: the translation key

Ideally, we would use the original CIR and DLM datasets directly for calculating LUC, but the two datasets substantially differed in their thematic resolution and in the implementation of land-use classes. This systematic difference can lead to a strong overestimation of LUC if it is not adequately accounted for.

1. Direct translation of CIR and DLM legends

We applied a direct semantic translation (Table S1) between CIR 2005 and DLM 2008 to test the thematic match between the two datasets. A good match would result in land-use changes between CIR 2005 and DLM 2008 in an order of magnitude typical for LUC dynamics in the region, *i.e.* well below 5 % of the area, reflecting the temporal mismatch of the datasets. A thematic mismatch would result in apparent LUC exceeding any reasonable observed dynamics.

Table S1: Semantic aggregation of DLM and CIR land-use classes

<table>
<tr><th colspan="2">DLM land use classes</th><th>CIR land use classes</th></tr>
<tr><td colspan="2">Cropland</td><td>Cropland</td></tr>
<tr><td colspan="2">Settlement</td><td>Settlement
Lawn</td></tr>
<tr><td colspan="2">Road Infrastructure</td><td rowspan="2">Settlement
Unknown</td></tr>
<tr><td colspan="2">Unknown</td></tr>
<tr><td colspan="2">Shrubs</td><td>Grove
Tree Row
Orchard Meadow
Bush</td></tr>
<tr><td colspan="2">Swamp</td><td>Swamp</td></tr>
<tr><td colspan="2">Grassland</td><td>Unspecified Grassland
Intensive Grassland
Mesophilic Grassland
Tall Herbaceous Vegetation</td></tr>
<tr><td></td><td>Wet</td><td>Wet Grassland
Periodically Flooded Grassland</td></tr>
<tr><td colspan="2">Forest</td><td>Deciduous Forest
Mixed Forest
Coniferous Forest</td></tr>
<tr><td></td><td>Wet</td><td>Wet Forest</td></tr>
</table>

The calculation of the apparent LUC between 2005 (CIR) and 2008 (DLM) is shown in a land-use matrix (Table S2).

Between CIR 2005 and DLM 2008 the apparent LUC encompassed 10 % $year^{-1}$ and 1,240 ha $year^{-1}$ [Table S2]. The annual average land-use change rate in Germany is 0.6 % (background data to the national inventory report [UBA, 2014]). Thus, LUC rates derived from direct translation are not reliable and a direct translation of CIR to DLM classes would result in a massive overestimation of LUC due to artefacts of thematic mismatch and other uncertainties such as spatial resolution.

Table S2: Matrix for detection of land-use change between the CIR 2005 and DLM 2008 datasets by direct translation
Grey cells represent congruent land-use classes according to Table S1 (no change) and thus are zero

	Settlement $_{DLM}$	Road Infrastructure $_{DLM}$	Cropland $_{DLM}$	Grassland $_{DLM}$	Wet Grassland $_{DLM}$	Garden $_{DLM}$	Swamp $_{DLM}$	Forest $_{DLM}$	Wet Forest $_{DLM}$	Shrubs $_{DLM}$	Wet Shrubs $_{DLM}$	Water $_{DLM}$	Area [ha]	Land use change [ha]	Land use change [ha year $^{-1}$]
Cropland $_{CIR}$	0.1			229.9				1.0		0.0		0.5	1,641.8	231.5	77.2
Settlement $_{CIR}$			0.2	1.4				0.1				0.0	20.8	1.8	0.6
Unknown $_{CIR}$	0.1			0.1								0.1	0.2	0.2	0.1
Grove $_{CIR}$	0.0		1.5	39.8	3.1			37.0	0.8			0.0	84.1	82.2	27.4
Tree Row $_{CIR}$				0.3				1.1					1.4	1.4	0.5
Orchard Meadow $_{CIR}$	0.7			0.1				0.0					0.7	0.7	0.2
Bush $_{CIR}$	0.0		1.5	19.0	2.7			6.9	2.5		1.7		35.4	34.3	11.4
Swamp / Fen $_{CIR}$			0.2	4.6	0.5			0.0	0.0			0.1	5.9	5.5	1.8
Unspecified Grassland $_{CIR}$		0.2											18.6	0.2	0.1
Wet Grassland $_{CIR}$	0.1		18.1	2,090.8			0.1	4.9	1.0	7.4		1.7	2,371.4	2,124.2	708.1
Intensive Grassland $_{CIR}$	1.2		399.9		84.2			5.7		0.1		2.6	4,404.2	493.6	164.5
Mesophilic Grassland $_{CIR}$	0.7		78.1		10.6	0.0		3.2	0.1	0.1		0.4	2,132.6	93.1	31.0
Lawn $_{CIR}$				0.8									0.9	0.8	0.3
Periodically Flooded Grassland $_{CIR}$			1.0	2.2								1.2	4.3	4.3	1.4
Tall Herbaceous Vegetation $_{CIR}$	0.7		19.6		53.0			28.0	1.1	22.4	0.6	3.1	495.3	128.5	42.8
Wet Forest $_{CIR}$			0.1	4.7	0.8		3.3	492.8		0.2	0.1	0.4	537.9	502.4	167.5
Deciduous Forest $_{CIR}$			0.4	4.6	0.2				3.4	5.5		0.4	615.3	14.4	4.8
Mixed Forest $_{CIR}$				0.1									31.2	0.1	0.0
Coniferous Forest $_{CIR}$			0.0	0.0									16.5	0.0	0.0
Research Area													**12,418.4**	3,719.2	1,239.7

To illustrate the effects of different translation approaches more effectively, we used the example of the ‘tall herbaceous vegetation’ class in a small part of the study area. Tall herbaceous vegetation indicates very extensive or abandoned grassland use, typically dominated by tall herbs rather than grasses, and often emerges under wet conditions. At the same time, tall herbaceous vegetation is diversely structured and thus difficult to identify by remote sensing. Tall herbaceous vegetation occurs in the CIR, but not in the DLM dataset. It belongs to the IPCC category of grassland and should theoretically also be represented as grassland in the DLM.

Here, we translated the CIR class tall herbaceous vegetation to grassland and calculated the LUC for this class from 1992 to 2000 by a direct comparison with the DLM (Fig. S1). As a result, 79.9 % of ‘tall herbaceous vegetation grassland’ would undergo land-use change, mainly to forest but also to cropland and settlement. The overall LUC rate appeared unrealistically high and suggested that the DLM systematically misclassified tall herbaceous vegetation grassland. The cropland and settlement parts in the DLM map are located adjacent to other croplands and settlements and could result from differences in spatial resolution between CIR and DLM. In conclusion, a large fraction of the LUC calculated by the direct comparison between CIR and DLM appeared to be an artefact. This thematic mismatch needs to be accounted for to generate realistic LUC rates.

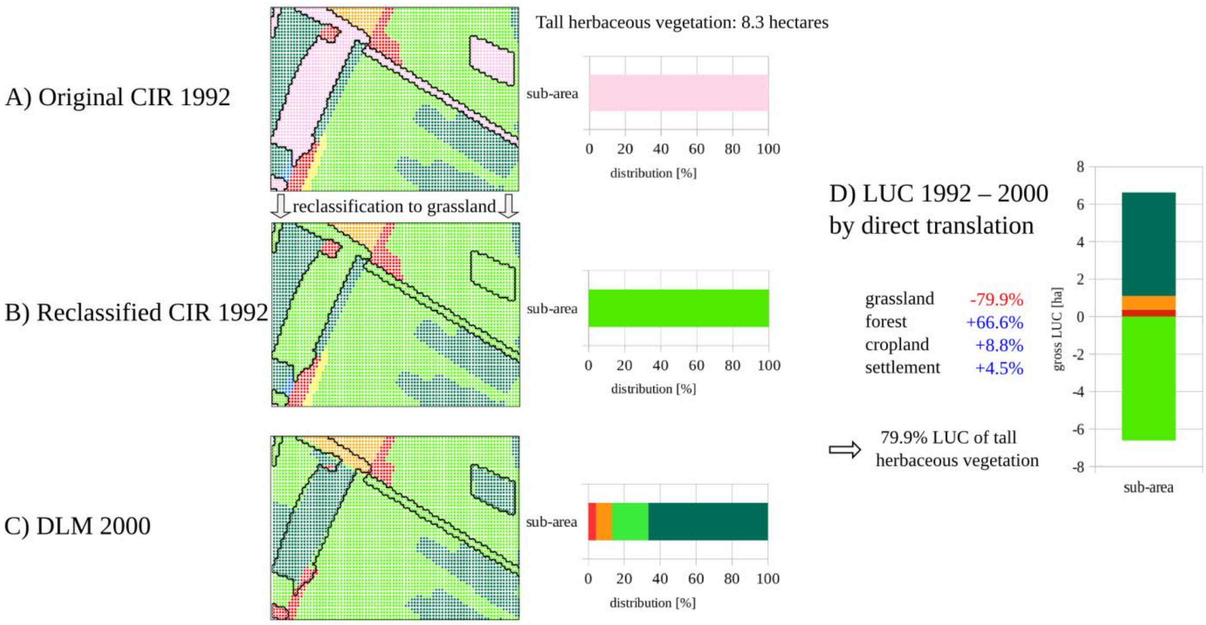

Figure S1: Work steps and result of the direct translation of CIR into DLM for the CIR class tall herbaceous vegetation

A) Original CIR map for 1992. The class tall herbaceous vegetation is highlighted as rose sub-area. B) Re-classified CIR map for 1992. The class tall herbaceous vegetation is reclassified to grassland in green. C) DLM land-use map for 2000. The original area of tall herbaceous vegetation is indicated by black boundaries. It contains as a mixture of forest, grassland, cropland and settlement. D) Resulting land-use change for tall herbaceous vegetation from 1992 to 2000 with the direct translation of CIR into DLM

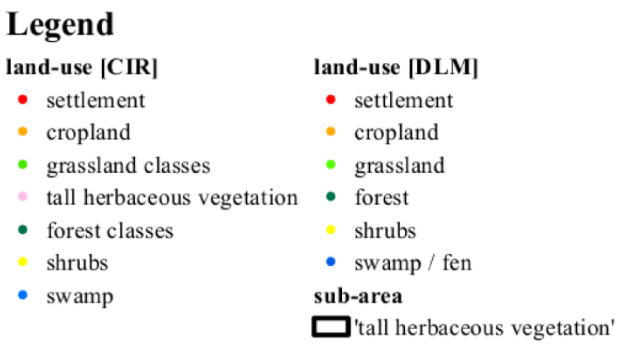

Figure S2: Legend to figures S1, S3 and S4

2. Quantifying the DLM misclassification: CIR 2005 *versus* DLM 2008

To quantify the thematic mismatch between CIR and DLM, we used the datasets with the best temporal match (see previous subsection), *i.e.* CIR 2005 and DLM 2008 (Fig. S3). The intersection resulted in a mix of DLM classes representing the CIR class tall herbaceous vegetation, the so-called 'translation key'. 69.4 % of tall herbaceous vegetation fell within the expected DLM category 'grassland'. 31.6 %, however, were classified as forest, cropland or settlement. This fraction indicated the thematic mismatch between CIR and DLM. Our best estimate for the real LUC could be calculated by subtracting the areas of the thematic mismatch from the LUC obtained by the direct comparison of CIR and DLM or, in other words, by applying the 'translation key'.

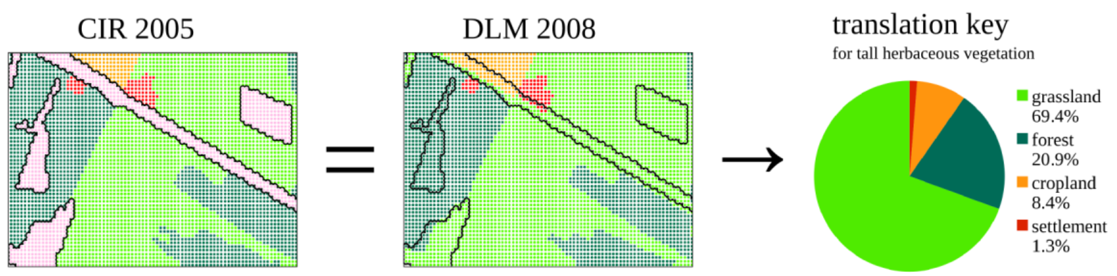

Figure S3: CIR 2005 compared with DLM 2008 for the CIR class tall herbaceous vegetation. The result generates a mix of DLM classes representative of the CIR class tall herbaceous vegetation, the so-called 'translation key'

As we used a sub-area to illustrate our methodology, the translation key for tall herbaceous vegetation shown in Figure S3 differed from the translation key for the whole study area.

3. Applying the translation key

The translation key was applied to calculate the LUC from 1992 to 2000, accounting for the thematic mismatch between CIR and DLM (Fig. S4). The translation key implied that the CIR class tall herbaceous vegetation would not entirely show up as grassland in the DLM, but would contain 31.6 % of other LU classes, *e.g.* 20.9 % forest due to the inconsistency between CIR and DLM (Fig. S4B). DLM 2000 showed 66.6 % forest in the original tall herbaceous vegetation area (Fig. S4C). Thus, 20.9 % of the forest was a definitional mismatch and 45.7 % was 'real' LUC (Fig. S4D). The translation key also reduced the artefact LUC to cropland and

settlement (compare with Fig. S1D).
In IPCC terminology, this is called ‘Approach 3’, which is spatially explicit (contains the boundaries within which certain a LUC occurs), but not fully geo-referenced. By comparing CIR 1992 with CIR 2005, the LUC could be verified in a fully geo-referenced way. Indeed, the large rectangular area with tall herbaceous vegetation in the west part of CIR 1992 (Fig. S4A) had been partly converted to forest in CIR 2005 (Fig. S4A), which was consistent with DLM 2008 (Fig. S3 centre).

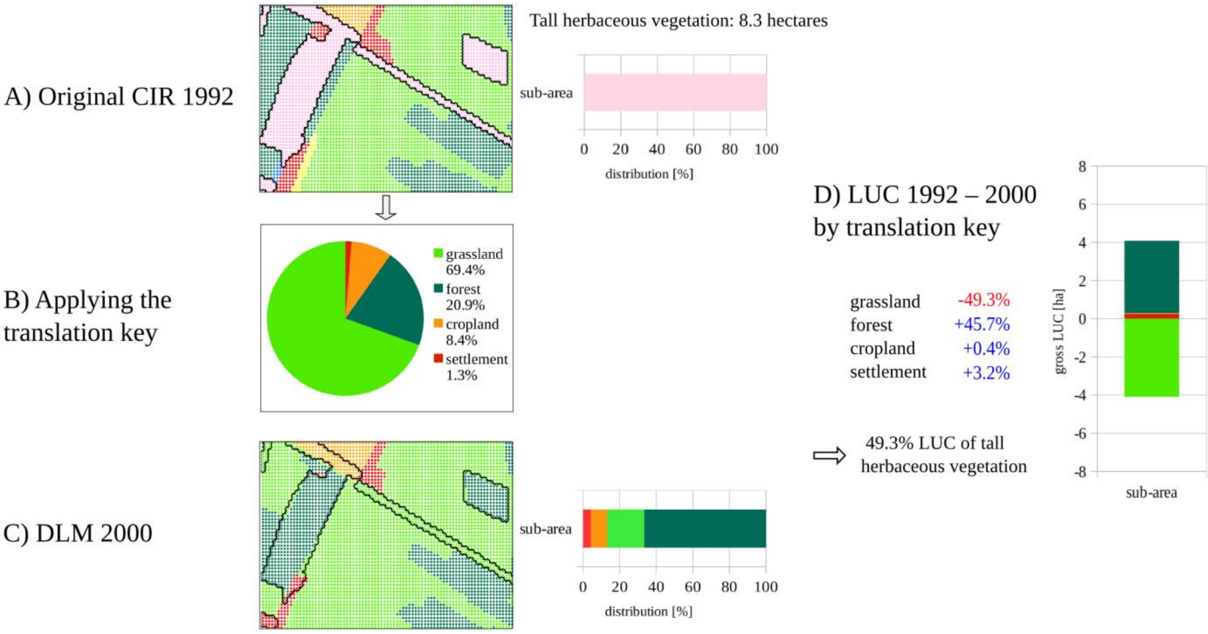

Figure S4: Work steps and result of the translation of CIR into DLM for the CIR class tall herbaceous vegetation by the translation key
A) Original CIR map for 1992. The class tall herbaceous vegetation is highlighted as rose sub-area. B) The translation key from CIR to DLM accounts for thematic mismatch. C) DLM land-use map for 2000. The original area of tall herbaceous vegetation is indicated by black boundaries. It contains as a mixture of forest, grassland, cropland and settlement. D) Resulting land-use change for tall herbaceous vegetation from 1992 to 2000 with the translation key

4. Handling of see-saw changes

A comparison of the rectangular area with tall herbaceous vegetation in the north-east corner of CIR 1992 (Fig. S4A) with the same area in DLM 2000 (Fig. S4C) and in DLM 2008 (Fig. S3 centre) revealed a shift from tall herbaceous vegetation in 1992 to forest in 2000 and back to grassland in 2008. As a forest is a long-term landscape structure, there is an obvious misinterpretation in DLM 2000. The translation key could partly correct a certain fraction of such a misclassification.
For the whole study area a few obvious misclassifications (268.7 ha; 2.15 %), as in this particular case, were manually corrected. By using a direct translation, an additional 803 ha (6.4 %) would undergo iterative see-saw changes in LU between 1992 and 2005, which was 41 % of the gross LUC (1935 ha; 15.5 %).

5. Deriving net and gross LUC

The methodology allows the detection of gross LUC in each period separately, but is unable to determine non-permanent LUC, *i.e.* whether an area is converted back to the original LU. To illustrate the calculation of the gross and net LUC translation key, an artificial example was generated. We assumed that two types of datasets (A and B) of different thematic resolution were available. We extracted 300 grid points from each dataset. Both datasets contained cropland (CL; orange grid points) and grassland (GL; green grid points). Dataset A was available at t_1 and t_2, whereas dataset B was only available at t_1. In this example we calculated LUC from A at t_1 (A1) to A at t_2 (A2) and from B at t_1 (B1) to A at t_2 (A2).
When using the consistent time series (A1 to A2), gross LUC from t_1 to t_2 encompassed 50 %, while net LUC was 0 % (Fig. S5).

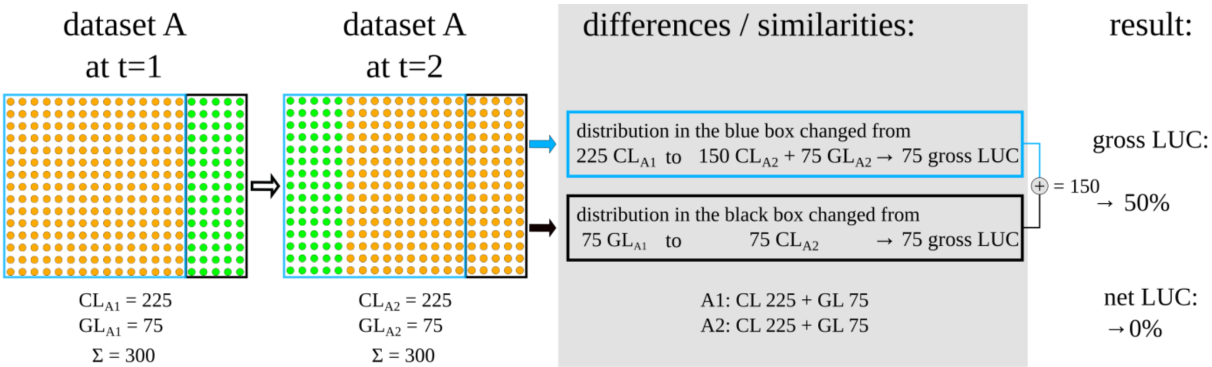

Figure S5: Work steps and result of comparing dataset A at t_1 with dataset A at t_2
Cropland in dataset A at t_1 (CL_{A1}) encompassed 225 grid points and is defined as 'blue box'. Grassland in dataset A at t_1 (GL_{A1}) encompassed 75 grid points and is defined as 'black box' for further analysis

If we wanted to analyse LUC of a time series between t_0, t_1, t_2, t_3, …, and dataset A were not available for t_0 and B were not available for t_2, t_3,…, we would need to analyse LUC from t_1 to t_2 by using both datasets. To do so, a translation key could be generated by using dataset A1 and dataset B1 (Fig. S6).

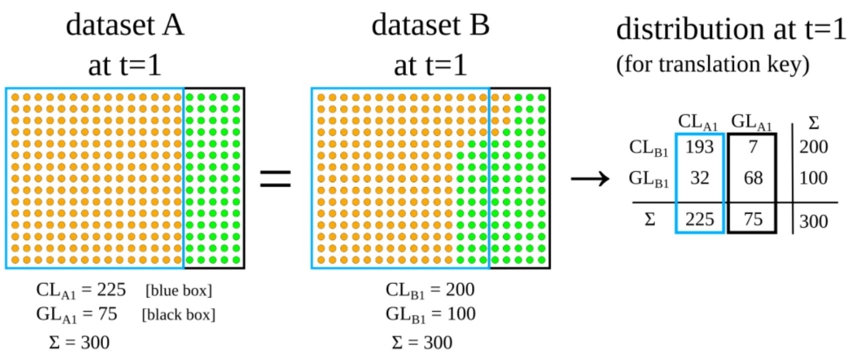

Figure S6: Representation of the translation key on dataset A at t_1 and dataset B at t_1
Plotting the number of grid points against one other produces a matrix which we termed 'translation key'. Cropland in dataset A at t_1 (CL_{A1}) encompassed 225 grid points and is defined as 'blue box'. Grassland in dataset A at t_1 (GL_{A1}) encompassed 75 grid points and is defined as 'black box' for further analysis

We then applied the translation key to calculate the LUC from B1 to A2. This resulted in a gross LUC of 45.3 % and a net LUC of 0 % (Fig. S7).

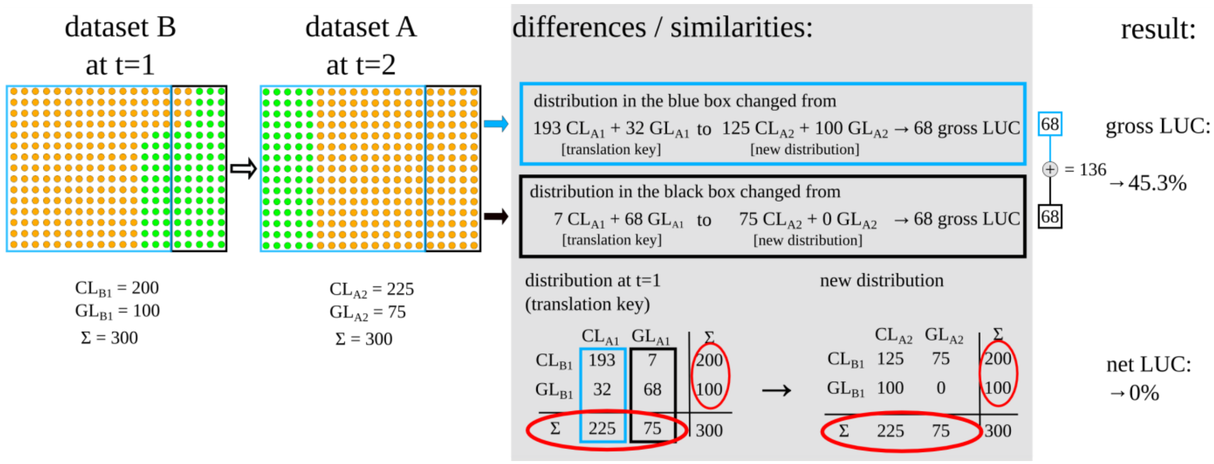

Figure S7: Land-use change by using the translation key (dataset B at t_1 and dataset A at t_2)
Gross LUC is calculated separately for the blue and the black box. The blue box represents cropland in dataset A at t_1 (CL_{A1}) and the black box represents grassland in dataset A at t_1 (GL_{A1}). Changes in the distribution by plotting $B_{t=1}$ against $A_{t=2}$ in comparison to the matrix of $B_{t=1}$ to $A_{t=1}$ indicate gross LUC. Changes in the sums of each land-use class in the matrix (red circle) indicate net LUC

A direct translation, assuming that cropland in datasets A corresponded to cropland in datasets B and grassland in datasets A corresponded to grassland in datasets B, could produce artefacts. The calculation of LUC from B1 to A2 by direct translation not only resulted in an overestimation of gross LUC, but also in an apparent net LUC of 8.3 % (Fig. S8).

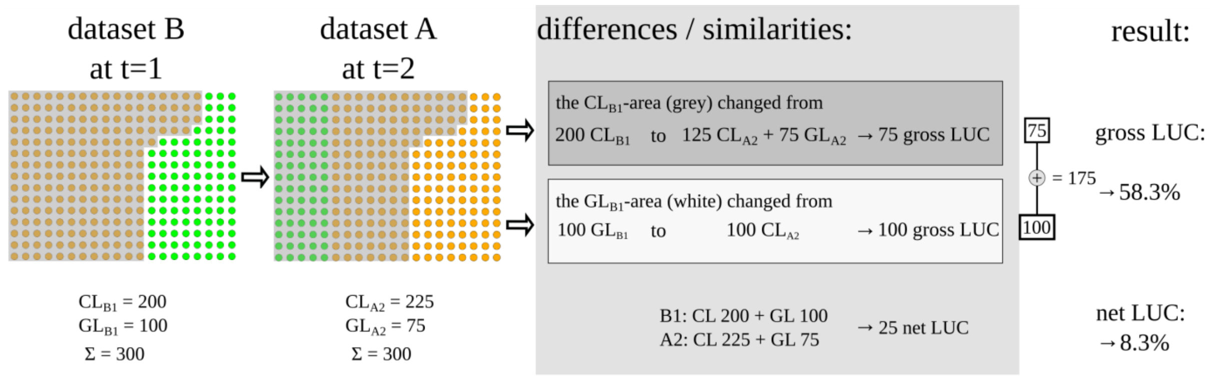

Figure S8: Land-use change by direct translation (dataset B at t_1 and dataset A at t_2)
The grey box represents cropland at t_1 and the white box represents grassland at t_1. Changes in the sums of each land-use class indicate net LUC

While the translation key might underestimate gross land-use change, the overestimation due to direct translation seemed to be higher and accompanied by apparent net LUC. When applying direct translation and the translation key to the cropland and grassland area of the whole study area (1992 to 2000), this resulted in gross changes of 846 ha and 192 ha respectively.

Groundwater table map

In the first step, a groundwater table map for the same period as the hydrogeological model (1993-2004) was created using average groundwater levels of the dipwells and the digital elevation model (DEM). The interpolation was performed by creating variograms followed by Kriging in Surfer [Golden Software Inc., 2009]. A comparison of the groundwater table map with the model showed only minor discrepancies related to local effects of weirs or ditches. The peat layer in the Drömling area is relatively shallow (0.3-0.5 m on average) and field observations did not show significant soil subsidence in the past 20 years. The error of using one DEM for the entire period instead of a dynamic soil surface model was therefore assumed to be small.

In the second step, the time series was split into three periods (Table 2) based on two criteria: first, the periods should match the periods for which LUC was calculated as closely as possible. Second, the climatic water balance (difference between precipitation and evapotranspiration) should be similar for all three periods to eliminate climatic variability and produce as pure a water management signal as possible. As a result, we calculated groundwater maps for the periods 1993 to 1998 (P 93-98), 1997 to 2005 (P 97-05) and 2004 to 2010 (P 04-10). Precipitation and evapotranspiration data were supplied by the German Weather Service at a spatial resolution of 1x1 km. The network of dipwells has gradually been extended. As there were fewer dipwells during the first and second periods, short time series were back-extrapolated under the condition of a correlation to a neighbouring dipwell of $R^2 > 0.7$. One exception was made for a crucial dipwell on the edge of the study area ($R^2 = 0.69$) Thus we used the same set of dipwells for all three groundwater table maps.