### RESEARCH ARTICLE



# Quantifying landscape-level land-use intensity patterns through radar-based remote sensing

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#### **Funding information**

Royal Society; Netherlands Organisation for Scientific Research

Handling Editor: Tomas Pärt

### **Abstract**

- The increasing availability of high resolution and high frequency, radar-based remote sensing data (i.e. observations on land surface characteristics, insensitive to cloud interference), makes it possible to track land-use intensity more precisely at the whole landscape scale.
- 2. Here, we develop a new radar-based remote sensing technique for large-scale quantification of agricultural land-use intensity across human-dominated land-scapes. We compare the respective abilities of Sentinel-1 C-band radar (C-SAR, C-band synthetic aperture radar) remote sensing data with the more traditional optical data, as MODIS enhanced vegetation indices (MODIS EVI), in capturing seasonality and the magnitude of land-use intensity (quantity and frequency of biomass removal). Linking our novel radar-based change detection algorithm to agricultural management activities on the ground, we quantify a whole landscape according to timing of mowing, a key grassland disturbance, thus capturing the dynamics of mowing regimes in grasslands.
- 3. We found that the radar-based proxy provides a rapid and reliable measure of landuse intensity, reliably predicting plant community composition at the landscape scale.
- 4. We tested this methodology using data on black-tailed godwits (*Limosa limosa limosa*), a specialist breeder of lowland meadows which, over the last 50 years, has shown dramatic declines. During territory establishment, black-tailed godwits preferentially used fields corresponding to intermediate radar-sensed land-use intensities. However, the present-day timing of mowing in these habitats was such that most godwit broods were less likely to be successful than broods in grasslands used at a lower intensity.
- 5. Synthesis and applications. The newly developed radar-based land-use intensity quantification is a powerful tool that makes it possible for ecologists and land managers to include agricultural land-use intensity measurements in population studies of the plants, insects, birds and mammals using these landscapes, at the spatial scale of entire populations. Applications of this tool include evaluating the effectiveness of European agri-environment schemes aiming to increase biodiversity

through decreased land-use intensity or expanding the quantification of agricultural land-use intensity to other geographic regions.

### KEYWORDS

black-tailed godwit, change detection, habitat preference, land-use intensity, MODIS EVI, mowing frequency, radar, remote sensing, Sentinel C-SAR, temporal stability

### 1 | INTRODUCTION

In light of the sheer magnitude and continued increase in anthropogenic-induced impact on Earth's ecosystems (Kareiva, Watts, McDonald, & Boucher, 2007; Vitousek, Mooney, Lubchenco, & Melillo, 1997), global indices generated from satellite remote sensing products are needed to provide early warnings for ecological functions that approach critical levels (Pereira et al., 2013; Skidmore et al., 2015). Agricultural food production is essential to human existence (Lambin & Meyfroidt, 2011; Tilman, Cassman, Matson, Naylor, & Polasky, 2002). However, modern agricultural practices rapidly degrade indispensable direct and indirect ecosystem services (e.g. water purification, soil nutrient recycling), that are paradoxically also essential for the production of healthy foods (Reganold & Wachter, 2016; Tilman, Balzer, Hill, & Befort, 2011). The current rates of biodiversity decline in agricultural landscapes are increasingly not accepted by society, and only land management practices which do not impair essential aspects of ecosystems functioning will be able to sustain the food demands of the future (Green et al., 2002; Lambin & Meyfroidt, 2011). Thus, there is an urgent need for the development of monitoring tools that capture land-use intensity from individual fields to the landscape scale and thus can assess the extent and effectiveness of nature-inclusive land-use practices.

The quantification of impacts of anthropogenic land-use intensity on declining biodiversity at high resolution for whole landscapes is poorly developed. Advances in global optical (colour-based) remote sensing techniques have been widely used to derive ecologically relevant information (Turner et al., 2003), e.g. pattern analysis tracking animal movement in relation to broad changes in vegetation productivity (Henry, Ament, & Cumming, 2016; Thorup et al., 2017). However, cloud interference especially in tropical and temperate climates limits the use of vegetation indices (such as MODIS NDVI and EVI products) in tracking seasonal vegetation changes at high temporal precision (Didan, Munoz, Solano, & Huete, 2015; Savtchenko et al., 2004). MODIS data products partially solve the problem of cloud interference by merging together the highest quality pixel data obtained from 16 daily passes (Didan et al., 2015). MODIS products are available since 2002 (Savtchenko et al., 2004), so they are now more suited for longterm trend analyses, quantifying habitat stability and detecting degradation (Wegmann, Leutner, & Dech, 2016), especially in the context of global change impacting ecologically sensitive landscapes (Skidmore et al., 2015; Turner et al., 2003).

In addition, global observational datasets collected by the C-band synthetic aperture radar (C-SAR) instrument on the Sentinel-1

satellite have recently become available at even higher spatial and temporal resolution than MODIS, observations that also happen to be insensitive to cloud interference (Snoeij et al., 2009). The C-SAR instrument actively emits microwave signals that penetrate the cloud layer to ground level. Microwave echoes received from multiple angles of the same position on the Earth's surface are synthesized to give a high-resolution coverage of surface structure on a single specific day (Snoeij et al., 2009). Therefore, this method captures the texture (surface roughness) of the vegetation instead of its colour. This is a great advancement on the multiday composites previously available from optical techniques. However, the detailed nature of the relation between C-SAR values and temporal proxies for vegetation greenness (MODIS EVI), ground measures such as vegetation composition, vegetation height and fluctuations in ambient temperatures, are yet to be established.

Grassland regions of north-west Europe represent an agricultural landscape now dominated by industrialized dairy farming (Bos, Smit, & Schröder, 2013). Farming practices involve the frequent application of artificial fertilizers and liquid manure injection, frequent mowing, repeated ploughing and reseeding of grasslands, use of herbicides to modify the plant community in favour of protein rich grasses, and the lowering of groundwater tables to facilitate heavy machinery (Bos et al., 2013; Groen et al., 2012). The timing of agricultural practices such as mowing for hay and silage is especially crucial to plants (Poschlod & Bonn, 1998) and animals (Beintema, 1986; Benton, Bryant, Cole, & Crick, 2002) that depend on these landscapes during the reproductive phase of their life cycle. European agri-environmental schemes aim to stimulate farmers to use more ecologically cognizant agricultural practices, in the hope of mitigating the negative environmental and ecological impacts from modern farming practices (Kleijn et al., 2006; Van der Geld, Groen, Veer, & Kemperink, 2013; Vickery, Bradbury, Henderson, Eaton, & Grice, 2004; Whitfield, 2006). However, studies assessing the effectiveness of agri-environmental schemes show that they perform poorly in promoting higher quality habitat or stabilizing effects on declining bird populations (Kleijn, Berendse, Smit, & Gilissen, 2001; Kleijn, Rundlöf, Scheper, Smith, & Tscharntke, 2011; Kleijn & Sutherland, 2003). Therefore, the development of a reliable and spatially explicit land-use intensity metric will be invaluable in assessing the effectiveness of agri-environmental schemes intended for improving biodiversity.

The continental black-tailed godwit (*Limosa limosa limosa*, Linnaeus, 1758) is a species that is now strongly declining due intensification of agricultural practices (Kentie et al., 2016). Over 80% of the East-Atlantic Flyway population of this species breed in The

Netherlands, individuals are relatively long-lived, site faithful (Kentie, Both, Hooijmeijer, & Piersma, 2014) and reasonably tolerant of landuse intensification (Bakker & Berendse, 1999). The Dutch population is currently estimated at 33,000 breeding pairs (Kentie et al., 2016), a considerable decline from 120,000 breeding pairs in the late 1960s (Gill et al., 2007; Mulder, 1972). It is widely recognized that the introduction of industrialized dairy farming practices has led to degradation of their herb-rich moist meadow breeding habitat (Groen et al., 2012; Kleijn et al., 2011; Newton, 2004), and the population continues to decline mainly due to reproductive failure (Beintema & Muskens, 1987; Kentie, Hooijmeijer, Trimbos, Groen, & Piersma, 2013; Roodbergen, van der Werf, & Hötker, 2012). Black-tailed godwits thereby serve as a good agriculture indicator species with which to test landscape metrics.

In this study, we develop novel remote sensing-based techniques to quantify land-use intensity across whole landscapes. We compare the optical-based (capturing vegetation colour) MODIS Enhanced Vegetation Index (MODIS EVI) 16-day time series with radar-based (capturing vegetation structure) Sentinel C-SAR 12-day time series in their respective abilities to capture seasonality and the magnitude of land-use intensity patterns. To gain insight into the range of habitat types that emerge under different land-use regimes, we link our novel radar-based land-use intensity data product to field observations on plant community composition. We use the black-tailed godwit as an ecological indicator to further test the method and develop management recommendations.

### 2 | MATERIALS AND METHODS

# 2.1 | Study site

The study was carried out in an area with modern dairy farming on a range of different soil parent materials (peat, sand and clays) in south-west Friesland, The Netherlands (52°55'N, 5°60'E), the study area encompassing 11,495 ha of agricultural land. Most of this land is managed as grassland for dairy farming, but dispersed throughout the area, arable fields are cropped for maize and tulips (Groen et al., 2012). The landscape is subdivided into individually managed fields (boerenbunder.nl, 2016; Kentie et al., 2014), with fields averaging  $3.54 \text{ ha} \pm 2.7 \text{ SD}$  (range 0.1-61 ha) in size, separated by ditches. Grassland management intensity ranges from fields that are frequently mown monocultures of ryegrass (Lolium perenne and Lolium multiflorum), with underground water drainage systems facilitating heavy machinery early in the season, to herb-rich semi-natural grasslands, with more than 10 grass and herb species (e.g. Anthoxanthum odoratum, Cynosurus cristatus, Lychnis floscuculi and occasionally Cirsium palustre and orchids) which are mown annually after 15 June and drained by surface foot drains (shallow ditches) (Groen et al., 2012).

Migratory black-tailed godwits arrive in the study area in early March when territories are established; first clutch initiation occurs from the first week of April and peaks around the middle of April. Chicks hatch from the last week of April, with peak hatching between 10 and 25 May, a second peak occurs in the last week of May,

associated with replacement clutch initiation. The main chick-rearing period is from mid-May to mid-June. Groups of adults leave to migrate southwards from mid-June to mid-July and juveniles from late-July to mid-August (Hooijmeijer et al., 2013; Kentie, Both, Hooijmeijer, & Piersma, 2015; Lourenço et al., 2011).

# 2.2 | Satellite remote sensing data

The C-SAR (10 m² resolution) radar data were obtained from the ESA Copernicus Scientific Data Hub (https://scihub.copernicus.eu/dhus/#/home) at 12-day intervals starting from the earliest reliable data 1 December 2015 until 31 August 2016. Data were preprocessed using Sentinel Application Platform Software V2.0.2 (Veci, 2015). Raw C-SAR data require several pre-processing steps to align consecutive scenes and project to the required map geometry. A series of online videos were used to guide the pre-processing of the raw radar imagery (https://www.youtube.com/watch?v=GPlU6-w\_5CE&list=PLi-1RJ8J3xJk2VHLXXJytwffpL\_yddjnd&index=1). A standard desktop personal computer was sufficient for processing the data for our study area. For study areas encompassing more than one satellite scene (i.e. >60,000 km² requiring scenes to be stitched together) necessitate access to a specialized data processing cluster.

MODIS EVI (250 m²) data were obtained from the NASA Earth Science Data portal (https://search.earthdata.nasa.gov) between 1 December 2015 until 31 August 2016 at 16-day intervals. Scenes with high cloud cover have poor data quality, therefore all high cloud cover pixels were removed (Didan et al., 2015). MODIS data were converted from the original compressed file format and pre-processed using online resources (https://github.com/cran/rts/blob/master/R/ModisDownload.R). Data were analysed using a standard desktop personal computer.

### 2.3 | Daily maximum temperatures

Daily maximum temperatures were obtained 1 December 2015 to 31 August 2016 from the Stavoren weather station situated within the south-west Friesland study area (https://www.knmi.nl/nederland-nu/klimatologie/daggegevens).

### 2.4 | Ground surveys and vegetation composition

We visited 641 fields located throughout the study area between 1 May and 15 June 2016. Habitat type was categorized into three types based on presence of characteristic plant species, following Groen et al. (2012) and Kentie, Valkema, van der Velde, Hooijmeijer, and Piersma (2015), as (1) botanically valuable and herb-rich combined (n = 241), (2) moderately herb-rich (n = 113) and (3) herb-poor (n = 287). Agricultural activities were categorized for all fields i.e. unmown, mown, vegetation regrowth, fertilizer application or ploughed. Within a subset of the survey fields, 55 detailed vegetation transects were carried out in the three habitat types, herb-rich (n = 32), moderately herb-rich (n = 13) and herb-poor (n = 10). Surface water from the fields was either drained by underground water drainage systems or

foot drains (ranging from shallow <10 cm to more distinct 10–30 cm). Plant species composition within the foot drains may differ from the drier and higher elevation stretches, due to the range in wetness. Therefore, to capture this variation in plant composition transects were orientated 20 m from the field edge (to avoid any edge effects) and perpendicular to the foot drains. At 1 m intervals along a 50 m tape measure, we lowered a 1 m vertical measuring rod into the vegetation to the soil and recorded all plant species that touched the rod (Table S1; Streeter, Hart-Davies, Hardcastle, Cole, & Harper, 2009) and measured plant height (±1 cm) by drawing the 10 closest leaves up to their full height around a measuring rod.

# 2.5 | Early territory establishment of black-tailed godwits

Each week between 14 March and 1 May 2016, a field team comprising eleven expert observers, located and counted black-tailed godwits for each field throughout the study area. Individuals and groups were categorized as territorial or flocks depending on their behaviour. For the analyses pertaining to black-tailed godwit distributions, only those individuals categorized as territorial (potentially breeding) were used.

### 2.6 | Data analysis

# 2.6.1 | Comparison between C-SAR, MODIS EVI and daily temperature range

To examine the nature of how MODIS EVI and C-SAR products were different, we created a dataset spanning 1 December 2015 to 31 August 2016. The values from the remote sensing products were calculated by extracting the mean value per parcel and averaged for each habitat type (herb-rich (n = 32), moderately herb-rich (n = 13) and herb-poor (n = 10). Daily maximum temperatures were averaged over 16 day periods and 12 day periods to coincide with the periodicity of the MODIS EVI and C-SAR data. We tested for individual responses for the three different habitats individually for MODIS EVI, C-SAR using ANCOVA (Crawley, 2005), and differences in habitat responses were established with Tukey HSD (De Mendiburu, 2013).

### 2.6.2 | Spatial change detection and ground survey

Temporal change detection analyses were carried out using successive C-SAR date pairs at 12-day intervals from 26 December 2015 to 17 July 2016. Change detection was calculated for each pixel ( $10 \text{ m}^2$ ), as  $\ln(t/t-1)$ , where t= time and t-1= the previous time period (Wegmann et al., 2016). "Change" values were then averaged for all pixels contained within each field boundary, since management—as mowing—was carried out at the scale of individual fields. Positive values corresponded to an increase in surface roughness (vegetation growth) and negative values corresponded to a reduction in surface roughness (winter frost periods and spring and summer management activities i.e. mowing, ploughing and harvesting of crops). Temporal stability of vegetation structure was summarized by taking the SD of the differences

in surface roughness during the black-tailed godwit breeding period (31 March-17 July—includes, clutch initiation to pre-migration staging), between 31 March and 17 July 2016. A one-way-ANOVA with a post hoc Tukey test (De Mendiburu, 2013), was used, with data extracted from 641 ground surveyed fields of known habitat, to establish the value range between habitat classes (herb-rich = 241, moderately herb-rich = 113 and herb-poor = 287). To compare the magnitude of difference in C-SAR values between habitat classes, effect sizes were calculated following Hedges, Gurevitch, and Curtis (1999).

# 2.6.3 | Vegetation composition

Plant species composition data were analysed using non-metric multidimensional scaling (NMDS) ordination of the transects based on Bray-Curtis similarity, a nonparametric measure that takes into account both rare and abundant species (Oksanen, 2011). Multiple environmental predictors, both from satellite remote sensing time series and vegetation transects were fitted to the first and second ordination axes using 1,000 permutations. Predictor data comprised: (1) Satellite remote sensing metrics; raw C-SAR and raw MODIS EVI corresponding to the closest date after which the vegetation survey was conducted, and temporal stability summarized by the standard deviation of change in C-SAR within the black-tailed godwit breeding period. (2) Vegetation transect metrics: plant community species richness and evenness as well as mean and standard deviation of plant height. All data were aggregated at the level of fields. The relation between the coefficient of variation in plant height and plant species diversity was analysed using linear regression (Crawley, 2005). A Spearman's rank order correlation was used to quantify the relation between the CV in plant height and plant species diversity (Crawley, 2005).

# 2.6.4 | Early establishment of territorial black-tailed godwits

The total number of territorial black-tailed godwits counted per week was used to calculate densities within the occupied fields. Manly's habitat selection ratios, a standardized index of habitat preference, weighted for differing densities of birds within occupied fields, were calculated per habitat type, following the methods described in Calenge (2006). Data were then pooled per habitat type for the 7 weeks of observation. A one-way-ANOVA with a post hoc Tukey test (De Mendiburu, 2013) was used to establish differences in godwit selection between habitat classes. To compare the magnitude of difference in selection between habitat classes, effect sizes were calculated following Hedges et al. (1999).

# 3 | RESULTS

# 3.1 | Comparison between C-SAR, MODIS EVI and daily temperature range

Comparing raw MODIS EVI (vegetation greenness) with C-SAR (surface roughness) and their relation to seasonal fluctuation in

ambient temperature (Figure 1), shows that MODIS EVI is strongly positively correlated with temperature (ANCOVA:  $F_{(1,52)}$  = 49.1,  $R^2$  = .47, p < .001). The differences between the three grassland habitats were not significant (Tukey HSD: p > .05). More encouragingly, a positive C-SAR response to increasing ambient temperature could be found only for the less intensively managed herb-rich parcels (p < .05), but not for more intensively managed moderately herb-rich and herb-poor parcels (ANCOVA:  $F_{(3,59)}$  = 3.9,  $R^2$  = .12, p < .05).

# 3.2 | Spatial change detection and ground survey

In the winter period 26 December 2015–31 March 2016, C-SAR values (indicating surface roughness) strongly declined (Figure 2, Table 1) in parallel with declining temperatures to a freezing period in February 2016. We observed one landscape-wide increase in surface roughness during the brief warm period, 19–31 January 2016, where 100% of the surface roughness in the study area increased after the freezing period (Figure 2, Table 1).

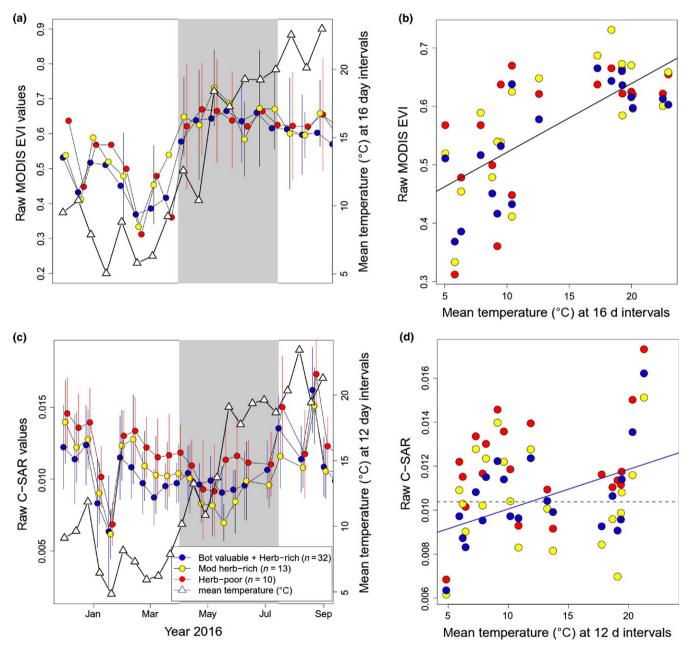
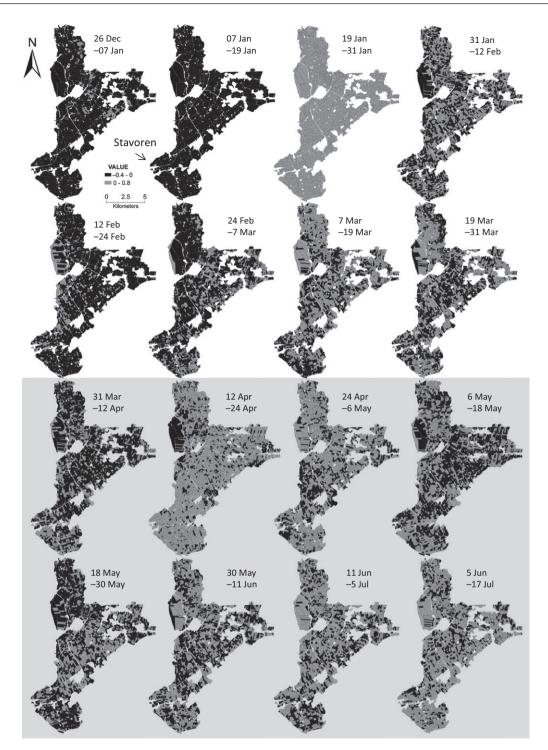


FIGURE 1 Comparing MODIS EVI and new C-SAR values separate for the three grassland habitat types. (a) Trends of MODIS EVI and mean temperature averaged over 16 days intervals. The grey background demarcates the black-tailed godwit breeding period (31 March-17 July 2016). (b) MODIS EVI positively correlates to increasing ambient temperature (solid black line). There were no significant differences between habitat types in the relation. (c) Trends of C-SAR values and mean temperature averaged over 12 days intervals. The grey background demarcates the black-tailed godwit breeding period (31 March-17 July 2016). (d) C-SAR values associated with herb-rich parcels significantly increase with ambient temperature (solid dark blue line). C-SAR values for parcels classified as moderately herb-rich and herb-poor were not significantly explained by temperature and were not different from each other (horizontal dotted line). C-SAR, C-band synthetic aperture radar [Colour figure can be viewed at wileyonlinelibrary.com]



**FIGURE 2** Spatial dynamics in surface roughness captured by the C-SAR, divided into two periods, (1) 26 December–31 March (white background), capturing winter dynamics with periods of freezing temperatures, and (2) 31 March–17 July 2016 (grey background), capturing spring and early summer and encompassing the black-tailed godwit breeding period from egg incubation to pre-migration staging. Fields coloured black represent a positive change in surface roughness (vegetation growth), fields coloured grey represent a negative change in surface roughness (winter frost periods, livestock grazing, mowing and ploughing). C-SAR, C-band synthetic aperture radar

As observed in the field during the ground surveys, large-scale mowing activities began in the first week of May 2016. This is reflected by a steep decrease in roughness (Figure 2, Table 1). During the period 6–18 May 2016, negative changes were recorded in 53% of the study area. In the following period, 18–30 May 2016, negative

changes, mainly be attributed to mowing and ploughing, were recorded in 59% of the study area. During the remaining period, 30 May–17 July 2016, the dynamics involved a continued spatial alternation between negative and positive changes in surface roughness (Figure 2, Table 1).

Habitat types relevant for meadow birds and plant diversity, as classified on the ground, were strongly predicted by the C-SAR standard deviation of change in surface roughness (Figure 3a,b; one-way ANOVA:  $F_{(2,639)}$  = 87,74, p < .001). Effect size analyses revealed a 0.27 ± 0.72 SE times greater variance in SD C-SAR values in moderately herb-rich fields and 0.39 ± 0.56 SE times higher in herb-poor fields compared to herb-rich fields.

## 3.3 | Vegetation composition

Non-metric multidimensional scaling ordination analyses of the vegetation community composition as measured on the ground in relation to satellite-derived remote sensing metrics, provided a 2D stress value of 0.16, representing a good fit of the model (Oksanen, 2011). We found that raw C-SAR and standard deviation C-SAR significantly explained the plant species community composition along the first axis (Table 2, Figure 4). Raw MODIS EVI, variation in plant height, plant species richness and evenness were not significantly correlated with the NMDS ordination values (Table 2). Within the grassland fields, we found that the ground-measured CV of plant height strongly positively related to increasing plant species diversity and independent of habitat type (Spearman's rank correlation:  $R_{\rm s} = .87$ , p < .001, Figure 5), so more structurally diverse fields were more species rich.

# 3.4 | Early establishment of territorial black-tailed godwits

Black-tailed godwits were observed establishing their breeding territories between 14 March and 1 May 2016 (Figure 6a), reaching

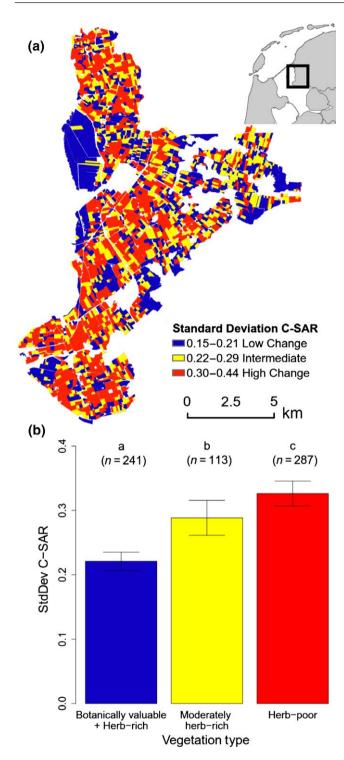
the highest densities between 11 and 18 April 2016 (Table S2). The godwits showed differences in their selection for the three habitat types (one-way ANOVA:  $F_{(2,18)} = 6.61$ , p < .01, Figure 6b). Effect size analyses revealed that, compared to the herb-rich fields (low change C-SAR), godwits show a higher (0.23  $\pm$  0.45 SE) selection for moderately herb-rich fields (intermediate change C-SAR), whereas they show a significantly lower ( $-0.37 \pm 0.36$  SE) selection for high change herb-poor fields (high change C-SAR).

### 4 | DISCUSSION

We compared the MODIS EVI and C-SAR time series in their respective abilities to capture seasonal and land-use intensity patterns. MODIS EVI values were strongly positively correlated with temperature. Therefore, EVI values capture the seasonal trends, but could not distinguish between the different agricultural land-use intensities. This makes MODIS EVI suitable for long-term analyses of trends in vegetation productivity (Wegmann et al., 2016), which enables landuse managers to detect landscape stability and degradation. C-SAR was sensitive to low temperatures (i.e. low C-SAR values <12°C). At higher temperatures (>12°C), the C-SAR could be used to detect sudden changes in above-ground biomass, particularly biomass removal through mowing, further we could distinguish between the mowing frequency of three grassland habitats with ground-truthed differences in community composition, resulting from different land-use intensities. Thus, the C-SAR time series showed good value as a tool to quantify land-use intensity. In our study, habitat type was most

**TABLE 1** Spatial dynamics in surface roughness captured by the C-SAR, showing the area (ha and percentage of the total study area) where positive and negative changes occurred (spatially represented in Figure 3). The table is divided into two periods, (1) 26 December–31 March, capturing winter dynamics with freezing temperatures, and (2) 31 March–17 July 2016 (grey background) capturing spring and early summer and encompassing the black-tailed godwit breeding period from egg incubation to pre-migration staging

	Positive change		Negative change	
Period	Area (ha)	Area (%)	Area (ha)	Area (%)
26 December 2015-07 January 2016	882	8	10,596	92
07-19 January 2016	176	2	11,302	98
19-31 January 2016	11,475	100	3	0
31 January-12 February 2016	5,828	51	5,650	49
12-24 February 2016	2,051	18	9,427	82
24 February-7 March 2016	3,412	30	8,065	70
07-19 March 2016	7,083	62	4,395	38
19-31 March 2016	6,576	57	4,902	43
31 March 12-April 2016	4,171	36	7,307	64
12-24 April 2016	8,776	76	2,702	24
24 April-6 May 2016	8,012	70	3,466	30
6-18 May 2016	5,354	47	6,124	53
18-30 May 2016	4,728	41	6,750	59
30 May-11 June 2016	6,510	57	4,967	43
11 June-5 July 2016	7,650	67	3,828	33
5-17 July 2016	8,483	74	2,995	26



**FIGURE 3** Temporal stability of vegetation structure summarized by (a) the *SD* of change C-SAR between 31 March and 17 July 2016, and (b) the range in *SD* C-SAR within fields classified into three habitat types. Error bars represent *SE*s and bars with different letters are significantly different (Tukey HSD, p < .05). Effect size differences, moderately herb-rich 0.27  $\pm$  0.72 *SE* and herb-poor 0.39  $\pm$  0.56 *SE* greater variance in *SD* C-SAR values compared to botanically valuable + herb-rich fields. C-SAR, C-band synthetic aperture radar

strongly predicted by "change detection analyses". The raw C-SAR values for herb-poor fields varied more widely and more frequently

than moderately herb-rich fields (reflecting more frequent mowing and higher productivity in the first type), while herb-rich fields remained the most stable.

The resulting spatial product capturing the magnitude of change both within each field and within the black-tailed godwit breeding period was the strongest predictor of plant species composition. In line with previous habitat quality studies of the area (Groen et al., 2012), fields with high variability in change detection values were strongly associated with species-poor fields dominated by L. perenne. Two groups of species were associated with low variation in change in surface roughness, plant species associated with high water-tables, e.g. Carex spp., Juncus effusus and Equisetum fluviatile and plant species found in the drier grasslands e.g. Rumex obtusifolius, Alopecurus pratensis and Lolium mulitflorum. Therefore, the magnitude of structural change determined with C-SAR, predicted the plant community composition. Thus, by generating an index that captures fortnightly and total variation per field, we accurately capture the total land-use intensity and associated habitat at the whole landscape level. This new index was then used to assess the potential for black-tailed godwits establishing territories for breeding.

During the breeding season of 2016, black-tailed godwits showed a higher than expected preference to establish territories in fields with intermediate land-use intensity and moderate herb-richness, followed by territory establishment in more stable herb-rich fields, with the lowest preference for establishing territories for highly disturbed, herb-poor fields. The first instance of large-scale mowing occurs within the first half of May, shown by a rapid reduction in surface roughness in 53% of the study area. This was directly followed by the second large-scale mowing event of 59% of the study area in the second half of May. This means that the timing of mowing, conducted by large heavy machines that directly remove all surface vegetation for silage, occurs during the peak incubation period of godwits and, indeed, other meadow birds. Nests are most vulnerable at this stage, since they may be destroyed by the mowing activities or discovered and depredated by avian predators, such as larger gull species that flock around mowing machinery. Therefore, C-SAR based quantification of the spatial dynamics in positive (growing vegetation) and negative (mowing and ploughing) changes that occur on the land surface at 12 day intervals, allows a spatial interpretation of the interplay between land-use intensity and the distribution of breeding territories of black-tailed godwits, or any other population that is studied.

In a recent study, Kentie et al. (2016) showed that between 2011 and 2015, black-tailed godwits have experienced an accelerated population decline of 6.3% per annum. With the remaining Dutch population comprising only 33,000 remaining breeding pairs, pro-active management of breeding habitat quality is necessary if we hope to reverse the current population trajectory. With these new analytical tools, it will be possible to focus protection measures (such as delayed management activities) in areas with high densities of breeding pairs during the critical nesting period. Precise locations of breeding pairs and the fate of broods are known from the detailed observations recorded by our field teams (Kentie, Both, et al., 2015), and these data

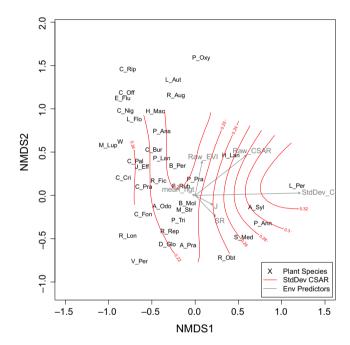
	NMDS1	NMDS2	R <sup>2</sup>	p-value		
Satellite remote sensing metrics						
Raw modis EVI	0.20	0.98	.03	.41		
Raw sentinel SAR1-C	0.79	0.62	.12	<.05*		
StdDev change sentinel SAR1-C	0.99	0.02	.31	<.001***		
Field transect measures						
Species richness	0.69	-0.72	.02	.55		
Species evenness	0.88	-0.48	.01	.78		
Mean plant height	-0.95	0.32	.00	.99		
StdDev plant height	0.67	0.74	.00	.96		

**TABLE 2** Regression table showing the fitted correlations of satellite remote sensing metrics and vegetation transect measures to the first and second NMDS ordination axes of plant species using 1,000 permutations

SAR, C-band synthetic aperture radar.

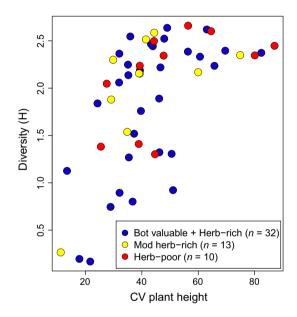
1284

Asterisks denote significant differences (\*p < .05, \*\*\*p < .001).



**FIGURE 4** NMDS biplot showing the Bray–Curtis dissimilarity scores of 54 plant species surveyed within 55-detailed vegetation transects conducted in May/Jun 2016. Plant Species abbreviations given in Table S1. Environmental predictors abbreviations: SR: species richness; J: species evenness, mean\_hgt: mean plant height, sd\_hgt: standard deviation of plant height, Raw\_EVI and Raw\_C-SAR: Raw EVI & raw C-SAR values on the closest date after vegetation transect survey, StdDev\_C-SAR: standard deviation of change calculated between date pairs of the C-SAR time series 31 March–17 July 2016. C-SAR, C-band synthetic aperture radar [Colour figure can be viewed at wileyonlinelibrary.com]

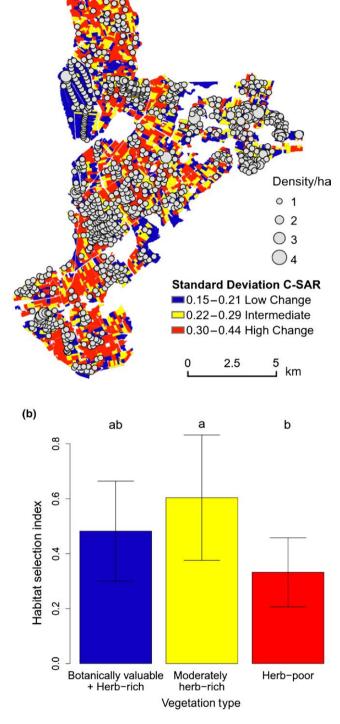
can now be assessed in terms of the neighbourhood, in terms of spatial resource availability (vegetation, i.e. as cover for pre-fledged precocial chicks and provider of insect food source) or threats to survival (rapid removal of vegetation). Reliable predictors for the quality of habitat at the landscape scale provide a much-needed tool in large-scale demography analyses, where population trends may be linked with changes in suitable habitat over time.



**FIGURE 5** Plant community diversity increases with increasing coefficient of variation in plant height, for three different habitat types (Spearman's rank correlation:  $R_s = .87$ , p < .001) [Colour figure can be viewed at wileyonlinelibrary.com]

### 4.1 | Management applications

Our new radar-based remote sensing method now allows land-use intensity to be included in the framework of essential biodiversity variables (Pettorelli et al., 2016), a minimum set of fundamental measures required to monitor and report on biodiversity change. This is of high ecological importance, as the timing of large-scale disturbances brought about by agricultural management disrupts the reproductive cycles of many species (Berendse, Chamberlain, Kleijn, & Schekkerman, 2004; Kleijn et al., 2001), resulting in continuing population declines with inappropriate management. We compared our method to the more classical medium resolution MODIS EVI data to study seasonal patterns of greenness under different management regimes, which can be important for predicting the spatial extent of potentially good



(a)

**FIGURE 6** (a) Average density per hectare and spatial distribution of black-tailed godwits sighted from 14 March to 1 May 2016, overlaid onto the *SD* C-SAR derived habitat types. (b) Differences in habitat selection between the three habitat classes. Error bars represent *SE*s and bars with different letters are significantly different (Tukey HSD, p < .05). Effect size differences, moderately herb-rich 0.23  $\pm$  0.45 *SE* higher and herb-poor 0.37  $\pm$  0.36 *SE* lower selection compared to botanically valuable+herb-rich fields. C-SAR, C-band synthetic aperture radar

quality habitat (Bell, Neal, & Medcalf, 2015; Scales et al., 2015; Thorup et al., 2017). We conclude the MODIS EVI data lack the temporal precision that we need for the reconstruction of the timing and magnitude of anthropogenic impacts. We show that the new C-SAR data are highly useful for precisely quantifying landscape-scale disturbance regimes, enabling reliable and continuous monitoring of the interplay between land-use intensity and ecological processes.

A spatially explicit land-use intensity index enables novel decision-making tools in land management planning, particularly where limited resources should be invested to achieve biodiversity targets. Specifically, ecologists and land managers can now include agricultural land-use intensity measurements at the resolution of individual fields yet at the spatial scale of entire populations in demographic and population studies of all organisms, whether plants, insects, birds or mammals, dependent on these landscapes. The new measures of land-use intensity can be incorporated into planning processes aiming to improve the quality of ecosystem functioning. For example, policy makers and land managers can conduct longer term spatial analyses, which evaluate the effectiveness of new agri-environment schemes. More practically, farmers and conservation agencies can access real-time spatial assessments of agricultural intensity for managing the spatio-temporal configuration of available breeding area.

#### **ACKNOWLEDGEMENTS**

We thank the following people for their invaluable help in the field: Mo Verhoeven, Jelle Loonstra, Wiebe Kaspersma, Ysbrand Galama, Haije Valkema, Egbert van der Velde, Guillaume Senterre, Marycha Franken, Atser Sybrandy, Sofia Briosa e Scheltinga. We thank Staatsbosbeheer, It Fryske Gea, Collectief Súdwestkust, and landowners for access to their land. We thank the editors and anonymous reviewers for constructive feedback. R.K. is funded by the Royal Society. Whilst the Province of Fryslân and the Dutch Ministry of Economic Affairs enabled the demographic work on the godwits, the funding for this study came from the Spinoza Premium Award 2014 to T.P. from the Netherlands Organisation for Scientific Research (NWO).

### **AUTHORS' CONTRIBUTIONS**

R.H., T.P. and H.O. conceived the ideas and designed methodology; R.H. and J.H. collected the data; R.H. and R.K. analysed the data; R.H. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

### **DATA ACCESSIBILITY**

Data are available from the University of Groningen Data Repository https://dataverse.nl/dataset.xhtml?persistentId=hdl:10411/B2VWDH (Howison, Piersma, Kentie, Hooijmeijer & Olff, 2017).

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**How to cite this article:** Howison RA, Piersma T, Kentie R, Hooijmeijer JCEW, Olff H. Quantifying landscape-level land-use intensity patterns through radar-based remote sensing. *J Appl Ecol.* 2018;55:1276–1287. <a href="https://doi.org/10.1111/1365-2664.13077">https://doi.org/10.1111/1365-2664.13077</a>