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Automatization and evaluation of a remote sensing-based indicator for wetland health assessment in East Africa on national and local scales

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ABSTRACT

To avoid wetland degradation and promote sustainable wetlands use, decision-makers and managing institutions need quantified and spatially explicit information on wetland ecosystem condition for policy development and wetland management. Remote sensing holds a significant potential for wetland mapping, inventorying, and monitoring. The Wetland Use Intensity (WUI) indicator, which is not specific to a particular crop and which requires little ancillary data, is based on the Mean Absolute Spectral Dynamics (MASD), which is a cumulative measure of reflectance change across a time series of optical satellite images. It is sensitive to the compound effects of land cover changes caused by different agricultural practices, flooding or burning. The more frequent and intrusive management practices are on the land cover, the stronger the WUI signal. WUI thus serves as a surrogate indicator to measure pressure on wetland ecosystems.

We developed a new and automated approach for WUI calculation that is implemented in the Google Earth Engine (GEE) cloud computing environment. Its automatic calculation, use of regular Sentinel-2 derived time series, and automatic cloud and cloud shadow masking renders WUI applicable for wetland management and produces high quality results with minimal user requirements, even under cloudy conditions. For the first time, we quantitatively tested the capacity of WUI to contribute to wetland health assessment in Rwanda on the national and local scale. On the national scale, we analyzed the discriminative power of WUI between different wetland management categories. On the local scale, we evaluated the possible contribution of WUI to a wetland ecosystem health scoring system. The results suggest that the adapted WUI indicator is informative, does not overlap with existing indicators, and is applicable for wetland management. The possibility to measure use intensity reliably and consistently over time with satellite data is useful to stakeholders in wetland management and wetland health monitoring, and can complement established field-based wetland health assessment frameworks.

1. Introduction

Wetland area and quality are declining worldwide. Their unsustainable use has led to the degradation of many wetlands and the rapid dwindling of total wetland area, with inland wetlands being most affected (Davidson, 2014; Junk et al., 2013; Millennium Ecosystem Assessment (Program), 2005; IPCC, 2014; Schuyt, 2005). Wetlands support the livelihoods of local communities (Nabahungu and Visser, 2011; Sakané et al., 2013; Turyahabwe et al., 2013), and provide a range of more widely distributed benefits to humankind, including biodiversity, water storage, water purification, flood mitigation, and food provision (Junk et al., 2013; Keddy et al., 2009; Langan et al., 2018).

Wetlands cover roughly 7% of the African continent (Junk et al., 2013) and due to their fertile soils and higher water availability, they are

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increasingly developed for agricultural use to counteract dependency on global food markets and reduce hunger and poverty (Dixon and Wood, 2003; Rebelo et al., 2010; Rodenburg et al., 2014). Africa has the lowest self-sufficiency rate in cereals and, without increasing agricultural productivity through intensification and further expanding cropland area, will progressively suffer from food price volatility and food insecurity (van Ittersum et al., 2016). Therefore, using African wetlands to increase food supply without compromising their ecological functioning is interlinked with long-term food security goals (Dixon and Wood, 2003). Yet, agricultural use is among the main drivers of wetland degradation which have already caused great losses of wetland area across Africa (Chapman et al., 2001; Darrah et al., 2019; Junk et al., 2013; Mitchell, 2013). The degradation of wetland ecosystems leads to habitat fragmentation and biodiversity loss, and negatively affects agricultural productivity (Gordon et al., 2010; Leemhuis et al., 2017).

Ecosystem health has become a useful concept to qualify ecosystem state and functioning. During the last decade of the 20th century, the ecosystem health concept evolved as an analogy to human health, where healthy refers to a state of vigour and resilience to stress (Mallee, 2017). In contrast to the concept of biological integrity that relates to the naturalness of an ecosystem in an evolutionary sense, it employs a socio-ecological perspective on ecosystem use and assumes that long-term sustainable ecosystem management is possible (Angermeier and Karr, 2019; Mallee, 2017). Therefore, it has found widespread adoption in the context of ecosystem management where ecosystem health assessment can guide management decisions (Mallee, 2017).

Since ecosystems are complex, their health cannot be measured directly, but indirectly through indicators (Kruse, 2019). Quantified biophysical and socio-economic indicators, compared side by side (Sun et al., 2015) or in the form of composite health indexes (Wu and Chen, 2020), have been used to measure the health of wetland ecosystems. Wetland ecosystem integrity is threatened by unsustainable wetland use practices, for which Schuyt (2005) describes a lack of information as an underlying cause and encourages incorporation of the spatial dimension in planning and management processes. The East African countries of Kenya, Tanzania, Uganda, and Rwanda work with national wetland maps to better understand wetland occurrence, state, and changes and enable informed decision-making (Amler et al., 2015). Updating such maps in a consistent and timely manner represents a challenge in wetland mapping approaches (Steinbach et al., 2021). Thus, remote sensing technology provides the possibility to obtain consistent, continuous, low cost spatial and temporal information on wetlands. This implies a significant potential for mapping, inventorying, and monitoring wetlands, particularly if remote sensing information can characterise wetland use and condition (Amler et al., 2015; MacKay et al., 2009; Strauch et al., 2016). It can render data acquisition for these measurements more practical and automated, therefore resource efficient and has been identified as a source of information that deserves more attention (Beuel et al., 2016; Chen et al., 2019; Das et al., 2020; Higginbottom and Symeonakis, 2014; Marambanyika et al., 2017; Rashid and Aneaus, 2019; Sun et al., 2016; Wu et al., 2018).

Remote sensing has already been tentatively deployed in the WET-Health approach, a wetland health assessment framework developed by Macfarlane et al. (2009) specifically for African wetlands and originally designed as a practical, field-based framework to rapidly assess the ecological state of South African wetlands. The WET-Health approach was thereafter successfully applied in studies of selected wetlands in Malawi (Kotze et al., 2012) and Zimbabwe (Marambanyika et al., 2017). Beuel et al. (2016) and Behn et al. (2018) tested it in Uganda, Kenya, Tanzania, and Rwanda. The semi-quantitative method aims to provide a simplification of the complex wetland ecosystem processes that facilitates their assessment by field surveyors, who give health scores from 0 (unmodified, no impact) to 10 (completely modified, critical impact) in different categories. An overall average health score is then calculated from the separate wetland impact scores (Kotze et al., 2012; Macfarlane et al., 2009).

WET-Health assumes that some land uses have more detrimental effects on wetland status than others, and that within each land use, impact scores can vary due to differences in land use intensity (Kotze et al., 2012; Macfarlane et al., 2009). WET-Health by default uses remote sensing to facilitate the planning of field visits (Kotze et al., 2012; Macfarlane et al., 2009), and can use image-derived land use land cover (LULC) maps and digital elevation models (DEM) (Kotze et al., 2012; Macfarlane et al., 2020; Marambanyika et al., 2017). This current use of static spatial information in WET-Health does not account for wetland characteristics that have a temporal dimension, like the intensity of use within and across land use classes and their changes over time. As such, WET-Health has barely tapped the potential of remote sensing to estimate the impact of different types of wetland use. Steinbach et al. (2021) suggest two wetland-specific map products that capture spatio-temporal variability which are relevant in this regard: The Sentinel-2-based Wetland Use Intensity (WUI) captures spectral changes on the wetland surface over time, and the Sentinel-1-based Surface Water Occurrence (SWO) reflects presence of surface water over a given period of time.

This study builds on Steinbach et al. (2021) by quantitatively testing an adjusted version of the WUI layer in Rwanda. Since a core element of wetlands is the hydrological cycle (Guo et al., 2017; Mahdavi et al., 2018; Perennou et al., 2018) and a core element of the WET-Health approach is land use (Kotze et al., 2012; Macfarlane et al., 2009, 2020), we also test the influence of SWO-derived surface water regime and of land use on WUI. Thus, we evaluate how WUI can be deployed to complement and upscale wetland health assessments and provide reliable spatio-temporal information for the systematic assessment of wetland health.

2. Study area and data

2.1. Study area

Rwanda is located in East Africa and bordered by Uganda, Tanzania, Burundi, and the Democratic Republic of the Congo. Rwanda is among the most densely populated countries in Africa (UN DESA, 2020), and consequently, its natural resources are under significant pressure to cater to food, water, and energy needs. Wetlands play a crucial role in meeting those needs (Hove et al., 2011; REMA, 2009; REMA, 2021), and cover between 10.6% (REMA, 2008) and 14.3% of the country (Steinbach et al., 2021). Wetlands have progressively been included in policies to increase agricultural production (MINAGRI, 2018). Rwanda's Irrigation Master Plan shows that most of the irrigation potential in Rwanda lies in wetlands, making them a possible mainstay of food security (Malesu et al., 2010). Wetland agricultural development has therefore been a key element of agricultural development strategies (Malesu et al., 2010; MINAGRI, 2009; MINAGRI, 2011; MINAGRI, 2018).

The agricultural seasons are commonly subdivided into Season A (September to February), Season B (March to June), and the shorter Season C (July to September) which are related to the two rainy seasons from September to October/December and from February/March to May (Mohammed et al., 2016; Muhire and Ahmed, 2015). Wetland paddy rice is grown in Seasons A and B, vegetables and sweet potatoes are cultivated in Season C (MINAGRI, 2020) and perennial crops like sugar cane and tea are cultivated year round (Dufitumukiza et al., 2020; Veldman and Lankhorst, 2011). Other wetland activities include livestock grazing, fishing, papyrus and reeds harvesting, peat, clay and gravel extraction (Beuel et al., 2016; Nabahungu and Visser, 2011; Uwimana et al., 2018a; van Dam et al., 2011).

Three management categories subdivide Rwandan wetlands: use without specific conditions, use under specific conditions, and full protection (Government of Rwanda (GoR), 2010; REMA, 2008). Conditional use regulates drainage, agricultural use, and peat extraction in certain wetland types, including agriculturally used wetlands that support a fraction of natural vegetation. Wetlands within internationally recognized protection categories like Ramsar sites, national parks or

Table 1
Remote sensing input datasets used in this study with respective spatial resolution, sensing period, number of images, and source.

Dataset	Spatial resolution	Acquisition period	Number	Source
Sentinel-2 Level 2A	10 m (Bands 3, 4, 8) 20 m (Bands 6, 11, 12)	07/2019–06/2021	MQS: 50 images MQT: 43 images MQU: 49 images MRT: 53 images MRU: 44 images MTC: 50 images MTD: 92 images	GEE catalogue (Gorelick et al., 2017)
S2cloudless Cloud Probability	10 m	07/2019–06/2021	MQS: 50 images MQT: 43 images MQU: 49 images MRT: 53 images MRU: 44 images MTC: 50 images MTD: 92 images	GEE catalogue (Gorelick et al., 2017)
Sentinel-1 Ground Range Detected (GRD), Interferometric Wide Swath (IW) mode, Ascending	5 × 20 m, resampled to 10 m (VV)	07/2019–06/2021	Relative orbit no. 74 over Rwanda (2 tiles): 234 images	GEE catalogue (Gorelick et al., 2017)
Landsat 7 Enhanced Thematic Mapper (ETM+) Surface Reflectance (SR)	30 m (Bands 1–5; 7)	07/2012–06/2014	Path 172, Row 61: 8 images Path 172, Row 62: 11 images Path 173, Row 61: 6 images Path 173, Row 62: 7 images	GEE catalogue (Gorelick et al., 2017)
Landsat 8 Observation Land Images (OLI) Surface Reflectance (SR)	30 m (Bands 2–7)	07/2012–06/2014 07/2019–06/2021	Path 172, Row 61: 8 images Path 172, Row 62: 12 images Path 173, Row 61: 6 images Path 173, Row 62: 8 images Path 172, Row 61: 8 images Path 172, Row 62: 7 images Path 173, Row 61: 3 images Path 173, Row 62: 5 images	GEE catalogue (Gorelick et al., 2017)
PlanetScope Biannual Surface Reflectance Mosaics	4.77 m (Bands 1–4)	01/2020–06/2020	24 base map quads	Norway International Climate and Forest Initiative (NICFI) (Planet, 2021)

reserves, as well as important water sources and dam marshlands are under full protection (REMA, 2008).

Wetland use is putting wetland health under pressure. Agricultural use of Rwandan wetlands and adjacent uplands is associated with water contamination from farming inputs and with net negative water and nutrient yields and soil erosion (Karambizi et al., 2019; REMA, 2009; REMA, 2021; Uwimana et al., 2018b). Physical and chemical pollution from mining, industrial complexes, urban areas, waste disposal, and commercial large-scale farming compromise water quality (Nhapi, 2011), and illegal use of harmful chemicals in agriculture and industry occurs sporadically (Umulisa et al., 2020). Restoring degraded wetlands and reversing the impact on biodiversity, soils, and water supplies has to take biophysical and socio-economic factors into account and is often not completely possible, as in the case of the Rugezi marsh, a Ramsar site of international importance (Grundling et al., 2018; Hategekimana and Twarabamenye, 2007; REMA, 2009). While wetland development is a priority, the Rwandan wetland management includes both development and rehabilitation efforts, such as erosion control or the relocation of economic wetland activities and informal settlements out of degraded sites (Ministry of Environment, 2020; United Nations (UN), 2015).

2.2. Data

2.2.1. Remote sensing imagery

Table 1 gives an overview of the remotely sensed imagery used to compute and assess WUI. The Sentinel-1 and -2 imagery and Landsat 7 and 8 imagery were acquired through the Google Earth Engine (GEE) cloud processing platform's data catalogue. The WUI layer was calculated from Sentinel-2 images with <40% cloud cover, processed to the bottom of atmosphere reflectance Level-2A, for seven tiles and acquired over two years, from July 2019 to June 2021.

Fig. 1 shows the footprints of the tiles. With two operational units, the Sentinel-2 satellite constellation has a revisit time of five days at the equator and delivers images at 10 to 60 m spatial resolution (Berger et al., 2012).

The s2cloudless dataset from the GEE platform provides cloud probability for each Sentinel-2 image (Skakun et al., 2022) and is used for cloud masking. Sentinel-1 Ground Range Detected (GRD) imagery in Interferometric Wide Swath (IW) mode from relative orbit number 74 was used for surface water detection and subsequent calculation of the Surface Water Dynamics (SWD) layer for the same observation period. The spatial resolution of this product is 20 m and is delivered resampled to 10 m in the GEE catalogue. As in Steinbach et al. (2021), only images in ascending mode were used, which are available every 12 days (Berger et al., 2012). Landsat 7 and 8 surface reflectance imagery at 30 m spatial resolution and a 16-day revisit time (Loveland and Irons, 2016) served for spectral comparison between the time of field data acquisition and the observation period. To maintain consistency in the length of image input period with the Sentinel-2 time series, the respective two-year time frames are July 2012 to June 2014 and July 2019 to June 2021. Landsat imagery below a cloud threshold of 20% was used, as this resulted in sufficient coverage for the subsequently created two composites while minimizing the probability of remaining artifacts after cloud and cloud shadow removal. For adjusting field data geometries to the reference period, the Norway International Climate and Forest Initiative (NICFI) Tropical Normalized Analytic Biannual best pixel composites at 4.77 m spatial resolution from January 2020 to June 2020 were downloaded via the Planet QGIS Plugin (Planet, 2021).

2.2.2. Rwandan wetland inventory and management categories

Information on wetland management was obtained from a dataset published in a ministerial order on the use of wetlands in 2010 (Government of Rwanda (GoR), 2010). This order officialised three management categories and is based on a national wetland inventory established by the Rwandan Ministry of Environment (MoE, formerly Ministry of Natural Resources of Rwanda, MINIRENA) and the Rwandan Environment Management Agency (REMA) in 2008. The inventory represents a baseline of all Rwandan wetlands, their use, importance (local, national, or international), size, location and suggested management category (REMA, 2008). Each wetland is allocated to a management category based on an evaluation of its bio-physical characteristics and its importance for the environment and human use (REMA, 2008). Between these categories, wetland sizes differ noticeably, as displayed in Fig. 2. While wetlands without specific use restrictions are generally small in size, wetlands under specific use conditions are on average roughly ten times larger. Fully protected wetlands have the widest size range, as they include small spring wetlands as well as large protected wetland complexes like the Akagera National Park which stretches along Rwanda's eastern border.

We use the 2010 spatial dataset and refer to it as the legally binding and spatially explicit management framework and not to other variable information that was captured in the wetland inventory in 2008. Although there is a more recent ministerial order from 2017, it largely confirmed the wetlands' respective management categories. Some exceptions are, for example, newly delineated wetlands or wetlands dis-associated from larger complexes (Government of Rwanda GoR, 2017). Since the 2017 dataset was not available as a spatial dataset but only in table format, we compared the spatial information in the 2010 dataset with the tabular information in the 2017 dataset and selected all wetlands that stayed in the same management category and for which the area did not change by more than ±15% as compared to the baseline. Thus, only wetlands consistent in managerial conditions and approximate boundaries between the two datasets were considered for further analysis.

2.2.3. *WET-Health field data*

According to the WET-Health approach, wetland health or the similarity to a wetland's reference condition, is assessed based on the assumption that human interference changes the natural quality and quantity of water and sediment flows, as well as the vegetation that wetlands carry. Therefore, the approach takes into account the four modules of hydrology, geomorphology, vegetation (Macfarlane et al., 2009), and water quality (Kotze et al., 2012). According to Kotze et al. (2012), Beuel et al. (2016), and Macfarlane et al. (2020), the following components should be assessed to determine the deviation from full wetland health:

- **Hydrology:** Intensity of irrigation and drainage management, assessed in terms of deviation from the natural level of wetness and the depth of drains and drain density
- **Geomorphology:** Increased erosion and/or decreased accretion, caused by land use practices like tillage or artificial drainage, which may result in erosion gullies
- **Vegetation:** Proportion of introduced to naturally occurring species, and invasion by alien or ruderal species; the intensity of cultivation practices
- **Water quality:** Water chemistry and suspended matter, as influenced by leaching from cultivated soils and runoff from roads or infrastructure

Indicators of human impact on wetland health are typically associated with particular land uses. Therefore, the initial methodology increasingly evolved to define literature and expert-informed scores per land use class, where the scoring is predetermined and merely adjusted

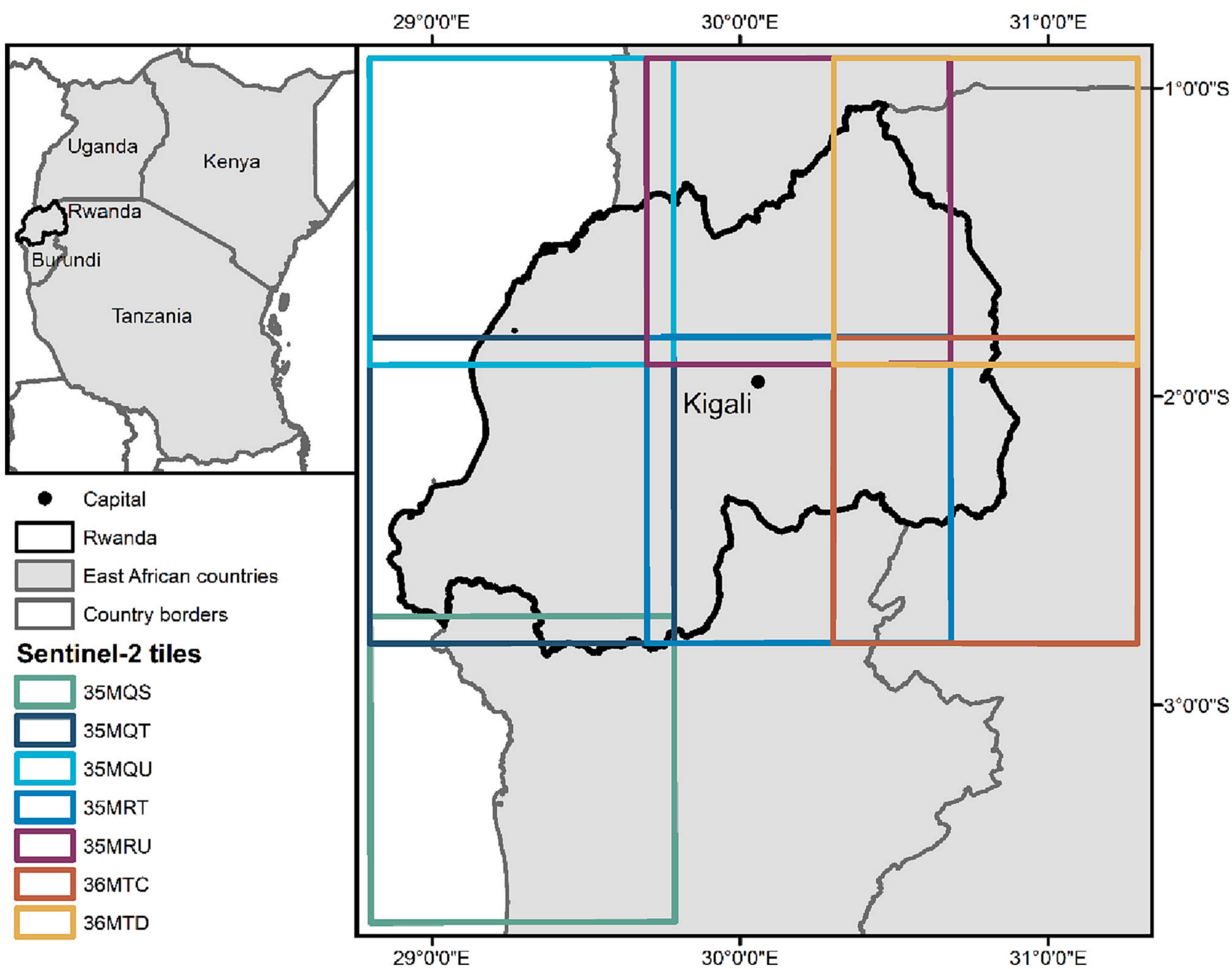

Fig. 1. Rwanda and the footprints of the Sentinel-2 tiles for which Wetland Use Intensity (WUI) was calculated.

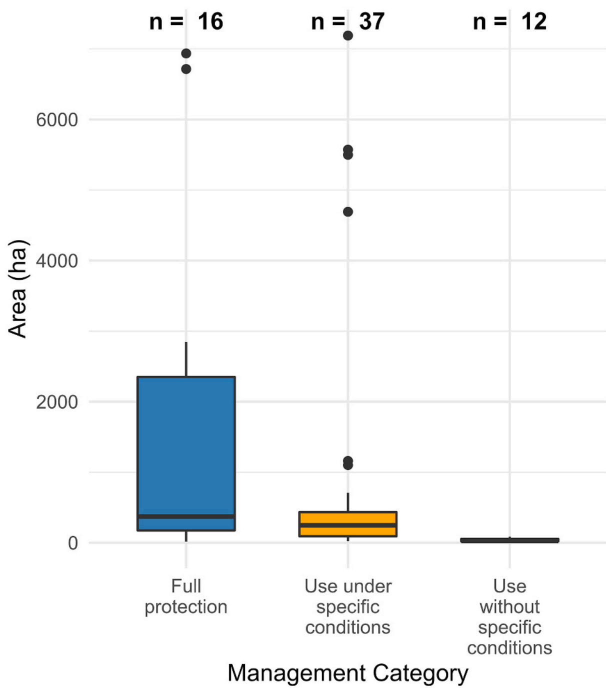

Fig. 2. Boxplots of lower boundary, median, and upper boundary of wetland sizes within the 95% confidence interval for the wetlands selected from the Rwandan national wetland inventory dataset.

according to the field assessment (Beuel et al., 2016; Macfarlane et al., 2020). A typical semi-natural wetland bearing reeds and grass vegetation could, for example, score an average of 1.5 (hydrology: 1, geomorphology: 0, vegetation: 4, water quality: 1) which is close to not being impacted. In contrast, homogeneous paddy rice agriculture could receive an average of 7.5 (hydrology: 10, geomorphology: 4, vegetation: 9, water quality: 7), which is a high impact score.

In this study, we use the WET-Health scoring sheet and method described by Beuel et al. (2016) who further adapted the approach by not considering hydrogeomorphic units (HGU), as proposed by Macfarlane et al. (2009), but randomly distributed plots of 250 × 250 m size as their reference unit. These fixed units provide good comparability and a well-adapted size for on-the-ground sampling. Within the plots, polygons of homogeneous land use were delineated and scores were assigned according to wetland condition. These scores were derived from the general impact of the respective land use on wetland health. They were slightly increased or decreased according to further site-specific characteristics (Beuel et al., 2016). The data created by Beuel et al. (2016) constitute part of this study's reference wetland condition dataset. A team of wetland experts collected these data during a field survey in the East African countries of Tanzania, Uganda, Kenya, and Rwanda in 2013. The Rwandan dataset consists of 19 plots that partially or fully cover wetland area, and of 34 polygons of homogeneous land use in wetlands. Land use within wetlands was categorized into classes as shown in Table 2. Beuel et al. (2016) did not record impact trends and did also not apply scoring to the catchment area.

This study's reference dataset was complemented with another 21 plots (36 more polygons) that were surveyed in the centre and along the roads towards the east and north of the country during a field visit in Rwanda in August 2018. The field survey was conducted based on the WET-Health protocol and land use impact score scheme as described by Beuel et al. (2016). The two wetland experts who conducted the survey were instructed by members of the 2013 field survey.

3. Methodology

3.1. Wetland Use Intensity calculation

For this study, we adjusted the WUI layer calculation as described by Steinbach et al. (2021), which is based on Mean Absolute Spectral Dynamics (MASD) (Franke et al., 2012), and automated it to be run on the GEE platform. WUI is a cumulative measure of reflectance change across a time series of optical satellite images. It is sensitive to the compound effects of land cover changes caused by different land management practices. Frequent and intrusive management practices on the land cover have a stronger WUI signal than rare events or marginal practices (Steinbach et al., 2021). In contrast to their method of using manually selected images that are spread out across the seasons, we considered all images below 40% cloud coverage for the study area between July 2019 and June 2021. Including cloudy images in the time series increases the number of observations, but requires thorough removal of clouds and cloud shadows. S2cloudless is a Sentinel Hub mono-temporal algorithm that uses machine learning on 10 spectral bands to detect clouds in Sentinel-2 imagery (Zupanc, 2017). S2cloudless has been shown to remove cloud reliably over different land covers and geographical regions, and to generally outperform the more cloud-conservative Sen2-Cor processor that is the ESA standard to generate Sentinel-2 Level 1C from Level 2A imagery (Skakun et al., 2022). We therefore selected this method to remove clouds and cloud shadow in the time series.

The GEE platform provides readily-processed s2cloudless cloud probability data for the complete Sentinel-2 time series, which employs standard values for the s2cloudless processor model variables (Skakun et al., 2022). However, the user can still define thresholds for cloud probability, near-infrared (NIR) reflectance for cloud shadow detection, and the maximum distance from cloud edges to search for cloud shadow when applying the s2cloudless algorithm on a Sentinel-2 time series in GEE, A buffer parameter lets the user define cloud edge dilation (Braaten, 2020). As this time series included relatively cloudy images, the minimum cloud probability threshold was set to a comparably low value of 20%. A maximum NIR value, the maximum distance for cloud shadows, and buffer parameters of 0.15, 1 km, and 50 m, respectively, yielded good cloud and cloud shadow masking results.

To avoid skewing the WUI values towards periods with more available cloud-free pixels, a regular time series of median composites was produced. Visual comparison of the composites showed that if they were based on one and two months of image acquisition across the year 2020, they still had too many gaps due to cloud cover, which resulted in artifacts in the WUI layer. Therefore, the observation period was set to two years, and bi-monthly composites were calculated from imagery from July 2019 to June 2021 to form a 2020 pseudo-year time series with six composites. This leaves the composites with nearly no missing data

Table 2
Land use classification in wetlands from the Rwandan WET-Health dataset by Beuel et al. (2016).

Level 1	Level 2
Agriculture	Homogeneous Heterogeneous
Grazing land	Pastures Pastoral rangelands
Semi-natural vegetation	Reeds, grassland Scrubland Natural forest, woodlands
Fallow	Long term Recently used
Mining	Brick making Quarrying
Industrial area	

pixels while still capturing annual hydrological and phenological variability. Then, the WUI equation was applied which is

$$WUI = \frac{1}{m-1}\sum_{t=1}^{m-1}\left(\frac{1}{n}\sum_{i=b}^{n}\left|\rho_i^t - \rho_i^{t+1}\right|\right)$$

where m = number of observation dates, t = observation date, n = number of spectral bands, i = index of summation, b = spectral band, and ρ = pixel reflectance. The input bands for Sentinel-2 derived WUI are the green, red, red-edge, NIR, and two short-wave infrared bands (SWIR) (bands 3, 4, 6, 8, 11, and 12). These bands are selected due to their sensitivity to vegetation and to represent a balance between the visible, NIR and SWIR wavelengths (Steinbach et al., 2021).

To test how the defined period may influence the resulting WUI values, WUI layers based on two-year inputs from January 2019 to December 2020 and from January 2020 to December 2021 were created, as well as a layer based on three years of Sentinel-2 inputs for the bi-monthly composites from January 2019 to December 2021. As the three layers based on two years of input data were highly correlated, it can be assumed that the approach is robust against slight temporal shifts in the observation period. Moreover, as the 2020 pseudo-year layer and the layer based on three years of input data were also highly correlated, it can be deduced that a larger timespan for the data inputs does not considerably change or improve the resulting layer values. This confirmed the validity of the chosen input data timeframe.

3.2. Surface Water Dynamics calculation

The timing and frequency of change in surface water represent a critical influence on wetlands and their land cover types and can be assessed with radar remote sensing (Muro et al., 2018). Temporal changes in surface water extent also potentially affect WUI values irrespective of actual land-use practices. To test for WUI sensitivity to the surface water regime, a Surface Water Dynamics (SWD) layer was calculated from Sentinel-1 imagery following the approach to compute Sentinel-1-based Surface Water Occurrence (SWO) as described by Steinbach et al. (2021). Accordingly, each Sentinel-1 scene was pre-processed and classified into water and non-water by applying the Otsu thresholding method (Otsu, 1979). Instead of creating a layer as the cumulative count of water presence per pixel, which is SWO, the pixel-wise changes from water (pixel value 1) to non-water (pixel value 0) or from non-water to water across the reference period were calculated by using an equation analogous to the WUI one:

$$SWD = \frac{1}{m-1}\sum_{t=1}^{m-1}\left(\left|v^t - v^{t+1}\right|\right)$$

where m = number of observation dates, t = observation date, v = pixel value. The result is a value between 0 and 1 with 0 indicating no changes within the observation period (always water or never water) and 1 indicating a change in every time step. The examples in Fig. 3 show WUI

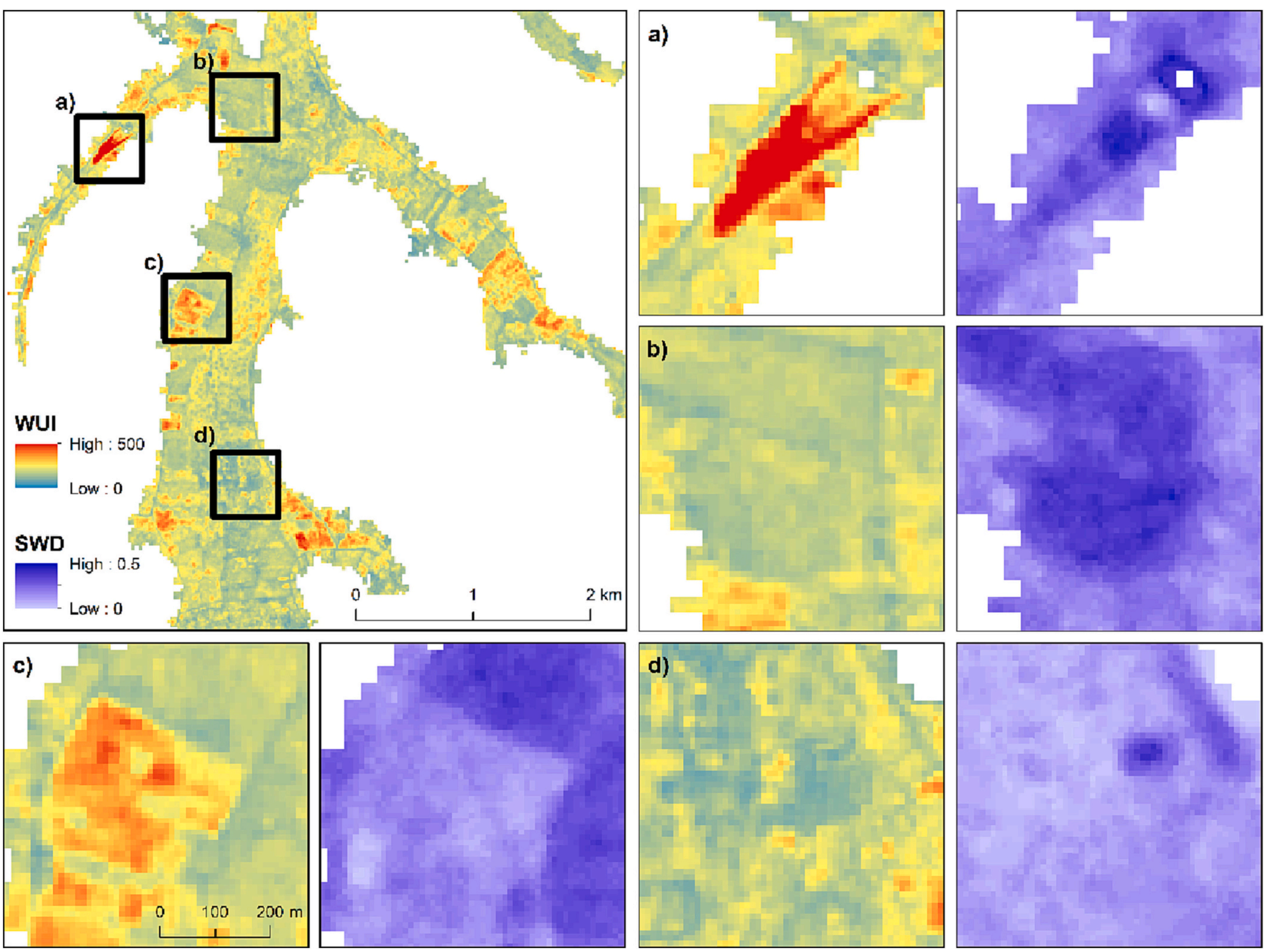

Fig. 3. Examples of Wetland Use Intensity (WUI) and Surface Water Dynamics (SWD) in north-eastern Rwanda, where a) Wetland Use Intensity (WUI) and Surface Water Dynamics (SWD) are both high, b) WUI is low and SWD is high, c) WUI is high and SWD is low, and where d) WUI and SWD are both low.

and SWD in a wetland in north-eastern Rwanda where a) WUI and SWD are both high, b) WUI is low and SWD is high, c) WUI is high and SWD is low, and d) WUI and SWD are both low.

3.3. WET-Health data

To obtain a consistent dataset that is suitable for the July 2019 to June 2021 observation period of this study, the 2018 WET-Health dataset first had to be created from the field data, and the 2013 one was checked and updated in terms of polygon geometry and spectral coherence.

The 2013 dataset was filtered to remove the industrial area class since buildings are expected not to change spectrally and therefore per se are not reflected in WUI. The remaining polygons were each compared to Google Earth's high spatial resolution imagery from within the study period, by using the time slider function. They were additionally compared to Planet's best pixel composites from January to June 2020 (Planet, 2021). Polygon boundaries were adjusted where homogeneous land use geometries differed from 2013, which could for example happen due to changed riverbed or agricultural expansion. Where land use changed altogether, polygons were removed (e.g., from wetland agriculture to a golf course).

We assessed the spectral similarity as another indication of the polygon's viability as a reference with a Change Vector Analysis (CVA) (Malila, 1980). First, Landsat 7 and 8 images (32 and 23 images per sensor, respectively) from a reference period of July 2012 to June 2014 were cloud-masked and a median composite was created. Then, for comparison to the spectral characteristics during the study period, 32 Landsat 8 images from July 2019 to June 2021 were cloud-masked and a second median composite created. The periods were chosen to be of similar length for comparability, to cover the whole study period, and to rule out phenological impacts on reflectance values. Lastly, the difference between the two composites was calculated and CVA was conducted on a difference image from the two composites, using all available bands in the visible, NIR and short-wave infrared (SWIR) domains. Due to the unimodal distribution of the difference image, Rosin thresholding (Rosin, 2001) was applied to differentiate between changed and unchanged pixels. Since the result showed only negligible changes in singular pixels within the WET-Health polygons, none of the remaining polygons were discarded.

To create the 2018 dataset from field data, high spatial resolution Google Earth imagery from the study period and Planet best pixel composites from January to June 2020 (NICFI) were interpreted to establish the homogeneous land use polygon boundaries within the plots. Scoring was done according to the land use impact on wetland condition and based on the preliminary scores from the field where we used the land use impact score sheet provided by Beuel et al. (2016). In the final merged reference dataset, each polygon represents a data point with WET-Health scores, mean WUI, and mean SWD. It contains a total of 65 polygons. The spatial distribution of WET-Health polygons for 2013 was random with a few adjustments based on field conditions (Beuel et al., 2016). This was not the case for the 2018 data set, but land use proportions were approximately the same in both data sets as displayed in Table 3, so that the overall proportion of the complete dataset can be described as representative of land use classes in the study area. An overview of the plot locations is presented in Fig. 4.

3.4. Evaluation of WUI for wetland health assessments

The calculation procedure of WUI (Steinbach et al., 2021) was adjusted to allow processing on a regular time series for a pseudo-year with two years of input imagery. Firstly, the result of the 2017 analysis was visually compared to the current 2020 layer concerning values, visible structures, and artifacts. However, no direct comparison of the methods is possible, since the Sentinel-2 time series over the study area in the GEE data catalogue, which the new method relies on, only starts in 2019. Therefore, the 2017 WUI layer from Steinbach et al. (2021) could not be recalculated with the new method.

Secondly, we plotted the WUI distribution within the official wetland management categories to evaluate how the WUI layer reflects wetland management at a national scale. The inventory includes the use without specific conditions, use under specific conditions, and full protection categories, which refer to increasing regulation and imply decreasing use intensity from the first to the last category. Since the wetland areas under the three categories largely differ in total area, random points were created within the Rwandan wetland area, labelled according to the management category, and 500 points per category were randomly selected. A density plot visualized the WUI values for these points and a one-way Analysis of Variance (ANOVA) was used to determine whether the difference between these categories was significant. To fulfil the requirement of normal distribution, the analysis was applied to the logarithmic values. Tukey's Honestly Significant Difference (HSD) Test determined post-hoc the patterns of difference between class means (Abdi and Williams, 2010). As a further statistical separability measure between management category distributions, we calculated the Jeffries-Matusita (JM) distance, which takes into account class mean and value distribution, and is commonly used to evaluate remote sensing-based classifications (e.g., Bruzzone et al., 1995; Dabboor et al., 2014; Dalponte et al., 2013; Visser et al., 2013). JM is implemented in the R package 'varSel' (Dalponte et al., 2013).

Lastly, the WUI layer was assessed at a local scale by comparing it to WET-Health field data. The reference for this variant of the WET-Health approach are areas of homogeneous land use within plots of 250 × 250 m size (Beuel et al., 2016). Therefore, the means of WUI and SWD were calculated for each WET-Health polygon. Correlation analysis between WUI and the WET-Health field data determined the association of WET-Health scores and WUI values, and correlation between SWD and WUI, as well as WET-Health scores the potential direct influence of the surface water regime on WUI values and WET-Health scores. As the Shapiro-Wilk test for normality showed that neither the WET-Health average and individual module scores, nor WUI and SWD polygon mean values were normally distributed, the non-parametric Spearman and Kendall correlation coefficients were employed. Since the logic of the WET-Health approach, in particular of its latest version, assumes a direct relationship between land use and wetland health (Macfarlane et al., 2020), we tested if land use is an equally strong determinant of WUI. In contrast to the WET-Health scores and SWD polygon means, WUI allowed for logarithmic transformation to normal distribution with equal variances across land use classes. Thus, we used a one-way ANOVA test for significant differences between land use classes.

4. Results

4.1. Comparison of the WUI calculation approaches

Fig. 5 shows a wetland in northeast Rwanda, which is a major rice growing area (Malesu et al., 2010), as represented in the 2020 WUI layer, in the 2017 WUI layer, and in the corresponding LULC layer from Steinbach et al. (2020). Most of the wetland area is classified as seasonally flooded agricultural land, but both WUI layers provide a more detailed account of the area. They display the structures of rice plots and

Table 3
Land use classes, number of WET-Health polygons with the contribution from the 2013 and 2018 datasets in parentheses, and number of pixels per land use class in the merged reference dataset.

Land use class	Number of polygons (2013/2018)	Number of pixels
Agriculture	31 (18/13)	7354
Grazing land	7 (4/3)	1502
Semi-natural vegetation	22 (11/11)	5950
Mining	5 (3/2)	187

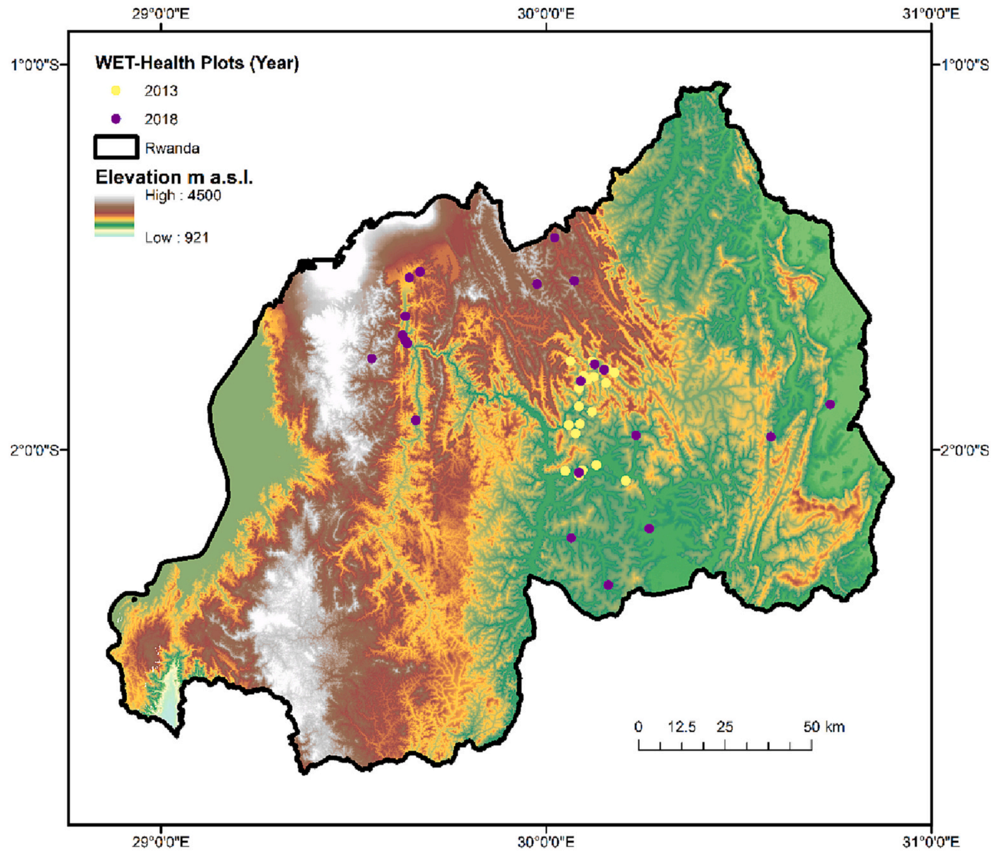

Fig. 4. Overview of the 250 × 250 m plot locations displayed as points for the 2013 (yellow) and 2018 (purple) WET-Health datasets. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

a gradient from higher to lower values from the northeast to the southwest. The 2017 layer has higher values in the northeast and lower values in the southwest, whereas the 2020 layer has relatively high values throughout. The WUI values of the latter range from 51.73 to 879.42, whereas the values of the former range from 48.00 to as high as 1210.20. The high values in the 2017 dataset could be artifacts due to missing values because of cloud cover, or the result of one of the input images capturing a peak time in the rice phenology of the fields in the northeast of that wetland. In both cases, it can be assumed that each input image has a higher impact on the resulting layer than in the case of the 2020 dataset. Here, the compositing approach and the larger number of input layers relativize phenological peaks or troughs. At the same time, while the semi-automatic approach captures the phenological peak in some plots, it misses the peak in other plots nearby, which may have theirs slightly earlier or later, due to different planting dates, varieties, or dates of fertilizer application. The automatic approach that uses bi-monthly composites ensures a more comprehensive temporal coverage, which may explain the evenly higher, but not extremely high WUI values in the 2020 dataset.

4.2. Ability of WUI to reflect wetland management practices

Fig. 6 shows density plots for the 500 samples per wetland management category as a representation of value distribution, their average values and standard deviations. Wetlands under full protection have the overall lowest values (mean = 141, std.dev. = 86). However, not the wetlands under conditional use (mean = 241, std.dev. = 140), but the wetlands under unrestricted use exhibit the next higher value range (mean = 179, st.dev. = 83). They also have the widest value distribution and the highest standard deviation. The one-way ANOVA showed that there was a statistically significant difference in logarithmic WUI values between at least two of the management categories ($F(2, 1497) = 116.5$, $p < 0.001$). Table 4 contains the results of the Tukey HSD test and the JM distances. According to the Tukey HSD test, WUI values differ significantly between each of the management category pairs, but the difference between the protected category to the other two is visibly more pronounced. The JM distance serves as another statistical measure between the WUI value distribution within the three management categories. It does not require normal value distribution and was therefore applied to the WUI values without logarithmization. The calculation results confirm the Tukey HSD test results. The distance is greatest between the protected and the conditional use categories with 0.53. The JM distance is lower the conditional and unrestricted use categories and lowest between the protected and unrestricted use categories, with 0.44 and 0.23, respectively.

4.3. Wetland condition assessment using WUI and the WET-Health approach

In Fig. 7, a scatterplot visualizes mean WUI per polygon against WET-Health average scores for each land use class, coloured according to land use class. WUI values in the agriculture class are the highest, averaging at 236.02, followed by mining with 215.81, grazing land with 202.76, and semi-natural vegetation with 185.22. Semi-natural vegetation and agriculture exhibit the highest standard deviations with 115.14 and 103.11, respectively, whereas standard deviations are markedly lower in the grazing land and mining classes with 56.98 and 43.67. Mining shows the smallest range of values for both WUI and WET-Health, with consistently high WET-Health scores and intermediate WUI values. Grazing land shows a wide range in both WET-Health scores and in WUI values, whereas agriculture and, except for two outliers, semi-natural vegetation cover a specific range in WET-Health scores, but a

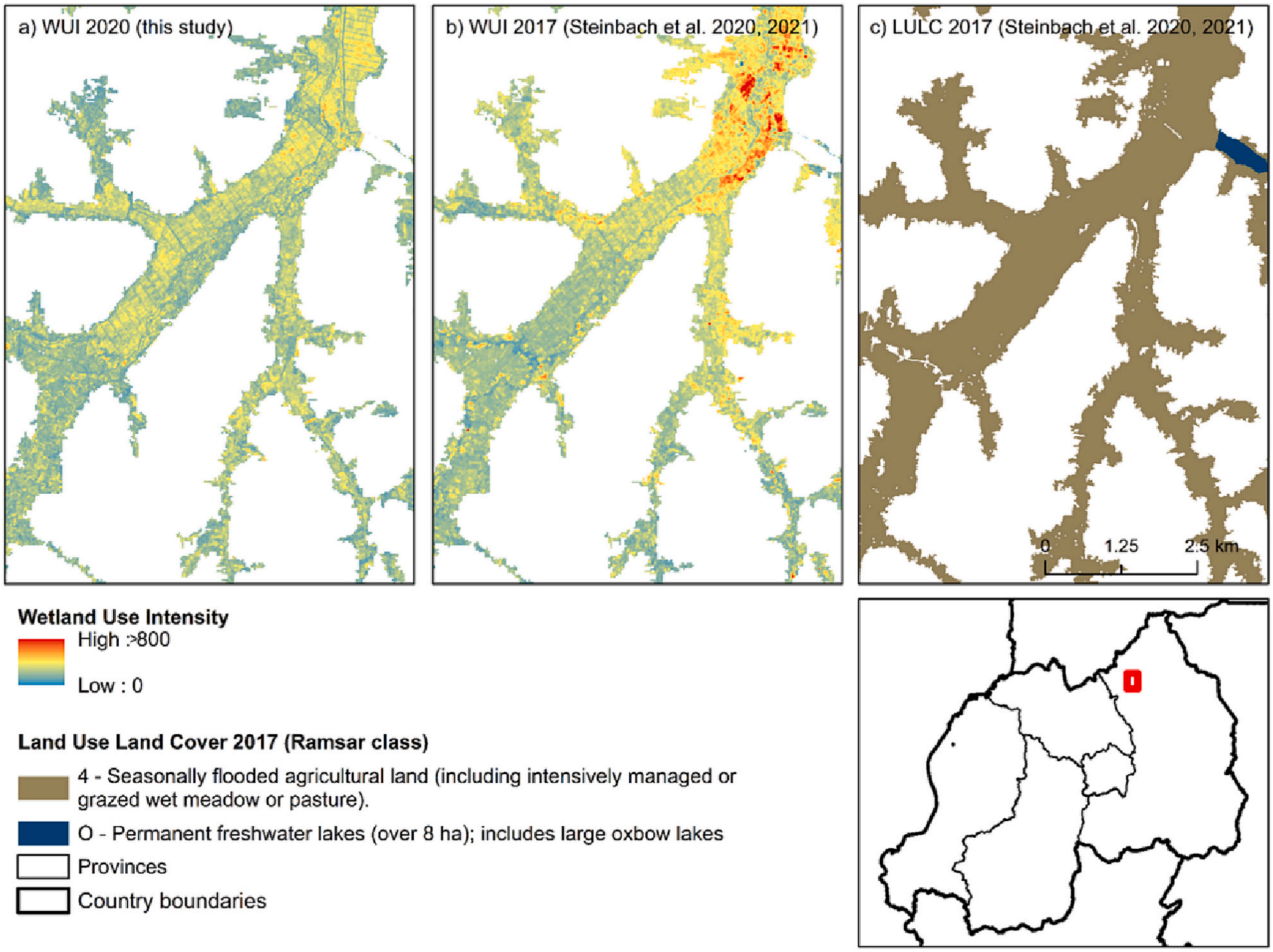

Fig. 5. Side-by-side zoom-in on a) the Wetland Use Intensity (WUI) layer from the 2020 pseudo-year and b) the WUI layer from Steinbach et al., 2021 which is based on manual selection and semi-automated cloud masking. C) shows Land Use Land Cover (LULC) from Steinbach et al. (2021, 2020).

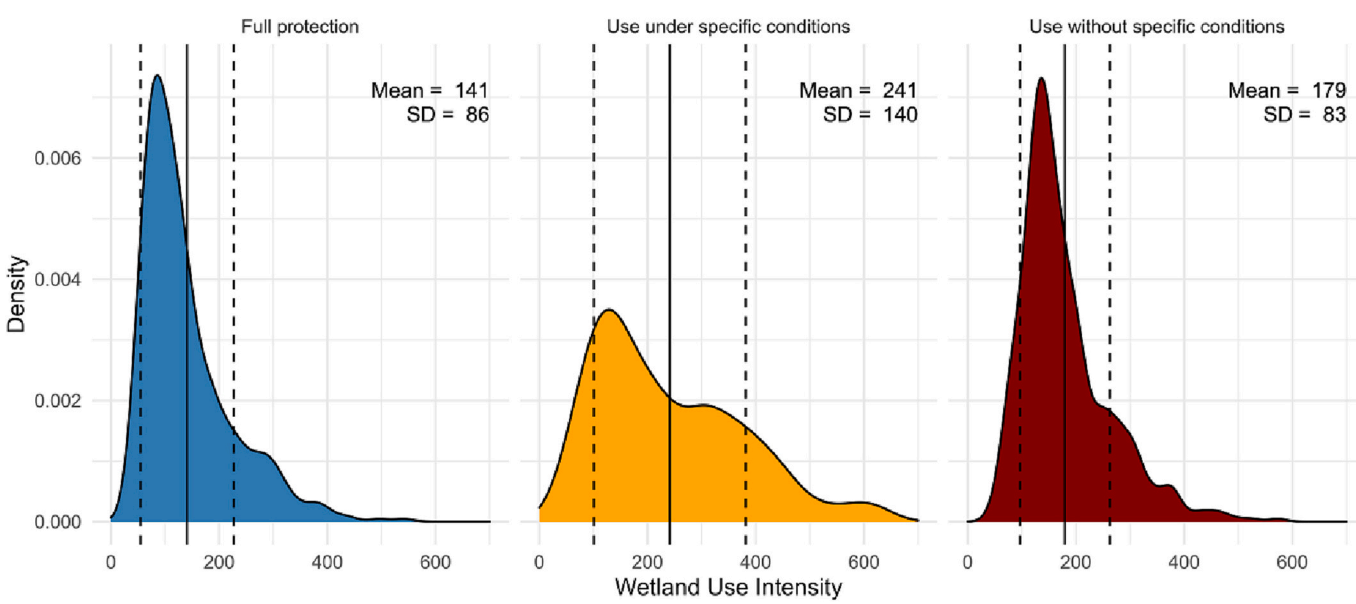

Fig. 6. Density plots of Wetland Use Intensity (WUI) value distribution within the wetland management categories protected, conditional use, and unrestricted use. Solid lines show the mean value for each category and dashed lines one standard deviation below and above the mean.

Table 4
Results of the Tukey Honest Significant Differences (HSD) test on the logarithmic Wetland Use Intensity (WUI) values across wetland management categories and Jeffries-Matusita distance between WUI values across wetland management categories.

Wetland management category pair	Tukey HSD difference of logarithmic WUI values ($p < 0.001$***)	Jeffries-Matusita distance of WUI values
Use under specific conditions / Full protection	0.51***	0.53
Use without specific conditions / Full protection	0.30***	0.23
Use without specific conditions / Use under specific conditions	−0.21***	0.44

wide range in WUI values. The result of the ANOVA on the logarithmic WUI values confirms that WUI values in none of the land use classes differ significantly from the values in one of the other classes ($F(3, 61) = 0.628$, $p = 0.6$).

The scatterplots of WET-Health averages and WUI against mean SWD in Fig. 8 a) and b) show no clustering according to the surface water regime. Little to highly dynamic surface water regimes occur across the whole WET-Health and WUI value ranges (0.25 to 9.5 and 81.99 to 503.11). Fig. 9 with a) Spearman and b) Kendall correlograms of SWD, WUI values, the four WET-Health module scores (hydrology – WH Hydro, water quality – WH Water, Vegetation – WH Veg, Geomorphology – WH Geom), and the average WET-Health score (WH Average) thus indicates no significant correlation between SWD and WUI, nor between SWD and the WET-Health module scores. In contrast, for both the Spearman and the Kendall tests for correlation, all WET-Health modules are highly intercorrelated at $\alpha = 0.05$. For both tests, the highest correlation occurs between the hydrology module and the average (Spearman: $r = 0.94$, Kendall: $r = 0.83$), whereas the lowest is found between the water and vegetation modules (Spearman: $r = 0.68$, Kendall: $r = 0.56$). The WUI values are correlated with part of the WET-Health module scores. They do not correlate with the hydrology and water quality module WET-Health scores, but are positively correlated with the geomorphology (Spearman: $r = 0.25$, Kendall: $r = 0.19$), vegetation (Spearman: $r = 0.26$, Kendall: r = 0.19), and average WET-Health scores (Spearman: $r = 0.27$, Kendall: r = 0.19). This correlation is significant, but a lot weaker than the intercorrelation of the WET-Health modules.

5. Discussion

5.1. Improvements through automating WUI assessment

Wetland development and agricultural intensification have the potential to increase economic output and improve food security in many African countries (Kwesiga et al., 2019; Kyalo and Heckelei, 2018; Rebelo et al., 2010; Rodenburg et al., 2014). Information on wetland condition is crucial to understand the impact that their development has on the ecosystem, and monitoring is required to ensure the effects stay within the desired boundaries. Remote sensing data can expand the spatial and temporal scales of field-based monitoring and thus enhance sustainability in spatial planning (Thamaga et al., 2021). A challenge to the adoption of remote sensing technology is the required technical

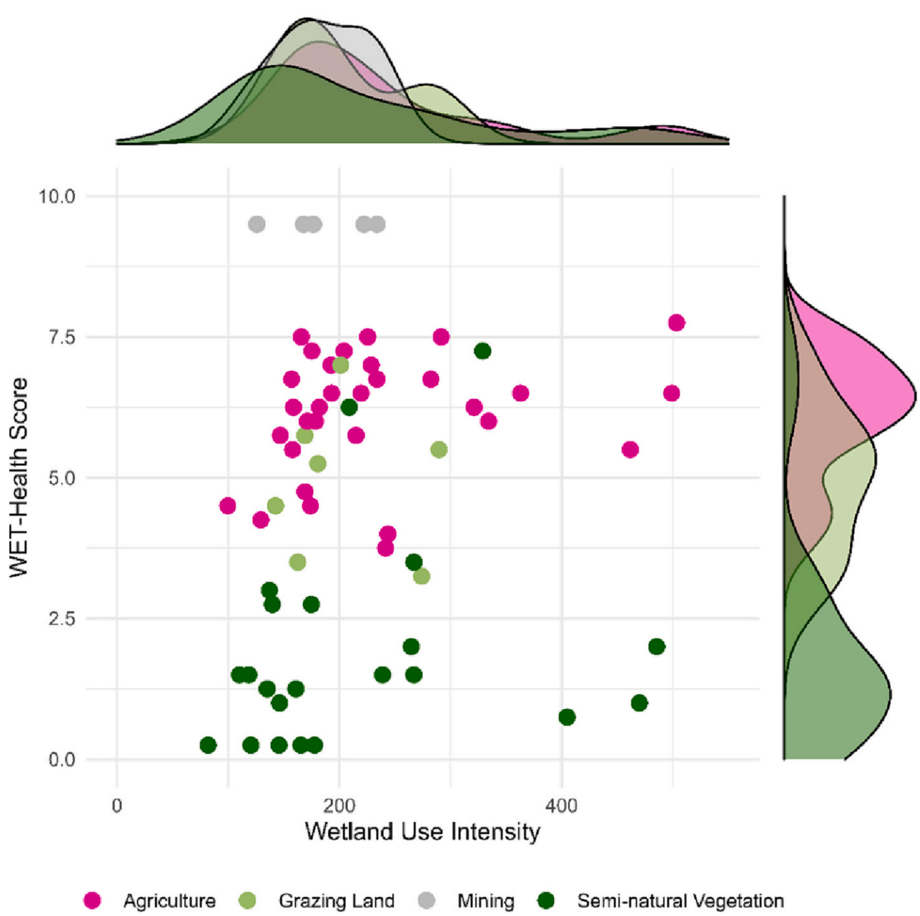

Fig. 7. Scatterplot with marginal density plots of Mean Wetland Use Intensity (WUI) and of the averaged WET-Health scores coloured according to land use class. As it is a constant value, no density curve for the WET-Health scores in the land use class "mining" is shown.

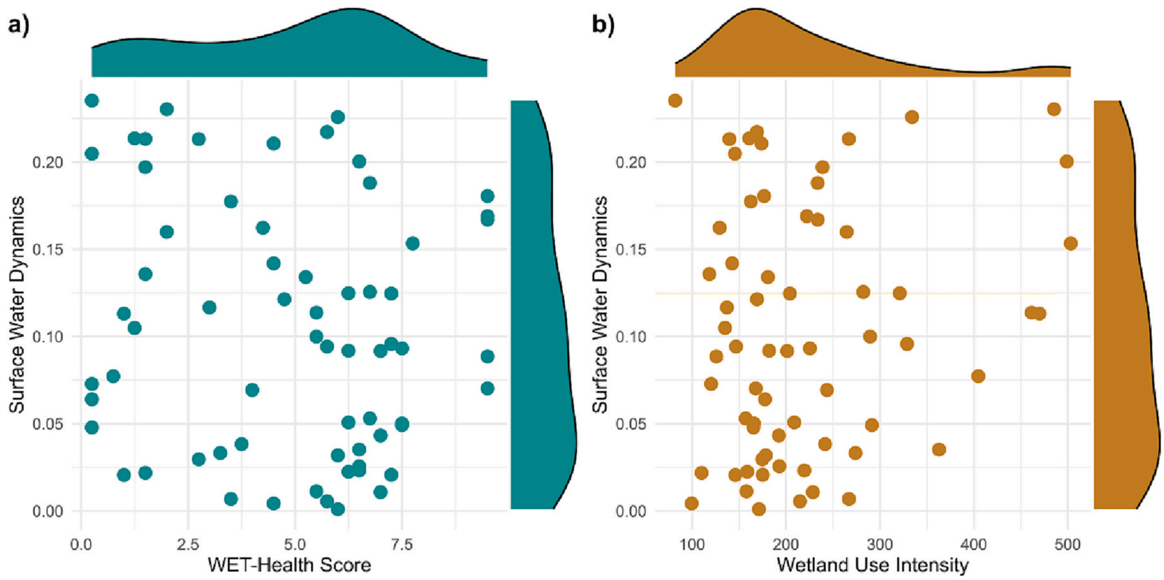

Fig. 8. a) WET-Health score and b) Wetland Use Intensity (WUI) plotted against Surface Water Dynamics (SWD), including their density curves.

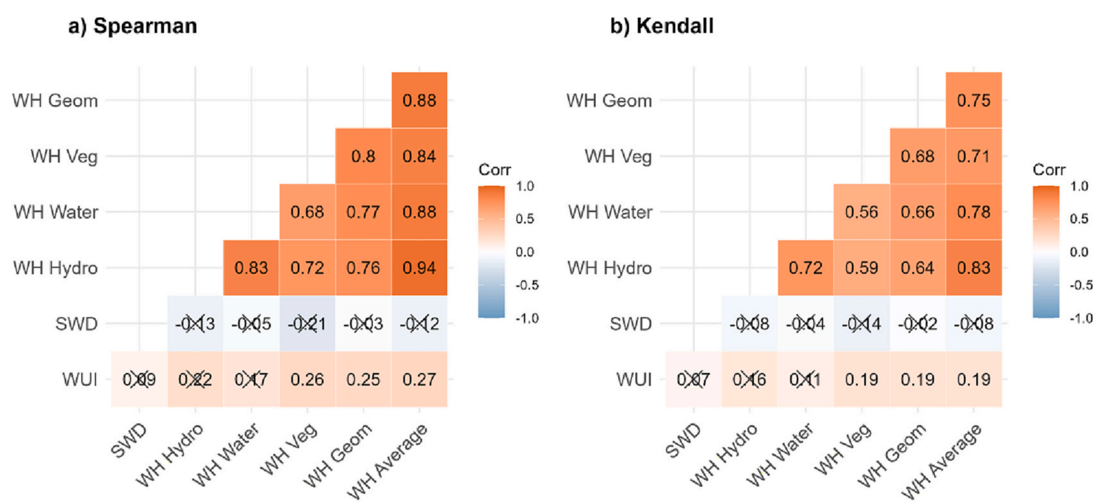

Fig. 9. A) Spearman and b) Kendall correlograms of mean Wetland Use Intensity (WUI) values per polygon and mean Surface Water Dynamics (SWD) with WET-Health scores in the categories hydrology (WH Hydro), water quality (WH Water), vegetation (WH Veg), geomorphology (WH Geom), and average (WH Average), at $\alpha = 0.05$. Non-significant correlations are crossed out.

capacities in planning agencies (Leemhuis et al., 2017; Nkundabose et al., 2020).

A key intention of developing a new and fully automated approach to calculating WUI was therefore to develop a meaningful remote sensing product related to wetland condition, and to make it more applicable and easy to use while increasing the number of input images and preserving or improving the informative value as compared to the semi-automatic approach suggested by Steinbach et al. (2021). When comparing the result to that of the initial calculation approach, only a few singular artifacts exist in both layers, proving the sustained layer quality. For the 2017 layer, the reason is missing observations in individual images and the relatively strong impact that these have on the result compared to the 2020 layer. For the 2020 layer, there are almost no missing values due to the compositing, although some artifacts occurred where cloud and cloud shadow were not properly picked up and masked by the automatic cloud masking method. In both instances, the WUI method captured spectral changes in wetland vegetation and water-relevant bands across the annual hydrological cycle and all three agricultural seasons (cf. MINAGRI, 2020). However, the new method required no further user input, pre- or post-processing steps, and can therefore be seen as more objective, more comparable, and robust across time steps. Moving the input period six months forward, backward, extending it to three instead of two years, and testing the results for correlation (which was high) all supported the robustness of the approach.

The main difference between the semi-automatic approach and the newly-developed automatic one is that the former is based on a maximum of 8 hand-picked images per Sentinel-2 tile, predominantly across the year 2017, with a few complementary images from 2016 to compensate for large gaps in the time series. The few remaining clouds and cloud shadows were removed with an object-based image classification approach and each one was verified manually. In contrast to this approach, the challenge of frequent cloud cover, which is also reported in other tropical wetland studies conducted with optical imagery (Hardy et al., 2020; Thonfeld et al., 2020b), is solved by increasing the number of input images through a higher cloud threshold, automatic cloud masking, and using a time frame of two years for bi-monthly composites which ensures a regular time series and improves the input image basis.

The new method for calculating WUI is fully automated in the cloud-based GEE processing environment, has low computational requirements, facilitating operational usage for wetland management. Various authors report a lack of applicability of geoinformation science outputs in operational wetland management (e.g., Hardy et al., 2020; Ludwig et al., 2019; Siles et al., 2019). Our automated method of generating WUI with open access spatial data that is globally available through long-term operational satellite platforms, and user-friendly, accessible software helps address this gap.

5.2. WUI for large-scale wetland health assessment in Rwanda

The importance of wetland ecosystem services is widely recognized, which entails the need for national wetland inventories and wetland condition monitoring (Muro et al., 2020; Rapinel et al., 2023). In Rwanda, the government regulates wetland use through different governmental institutions, which ensure that wetland resources are optimally used at the intersection of the different and partly conflicting wetland activities (Heermans and Ikirezi, 2015). Official categorization of wetland uses (Government of Rwanda (GoR), 2010) is supposed to help to keep wetlands in a healthy and thus productive condition in the long run (Heermans and Ikirezi, 2015; REMA, 2008).

Large-scale coverage of meaningful information on ecosystem condition is a critical ecological indicator requirement (Burgass et al., 2017), in particular when working on national scales. WUI can be calculated for large areas such as the whole of Rwanda, where WUI values show different distributions across the official wetland management categories. This suggests that the WUI layer is able to reflect wetland management practice regulations, assuming they are implemented according to the management plan. That the WUI values are inverted for the conditional and unrestricted use category, where more intensive management is allowed in the unrestricted use category, does not necessarily mean that WUI fails to reflect actual wetland management. The Government of Rwanda (GoR) categorizes wetlands according to certain characteristics and functions, and to what is evaluated to be an optimal use considering multiple factors (Government of Rwanda (GoR), 2010; REMA, 2008). Consequently, particularly the wide floodplain wetlands in the centre, south, and northeast of the country, which are well suited for intensive agricultural production, fall into the category of conditional use. In contrast, wetlands in the unrestricted use category are often narrow, overall smaller, and in many instances may not have the bio-physical characteristics that allow for intensive cultivation practices. Hence, WUI tends to be lower in these wetlands. An additional exploratory comparison of WUI values across a subset excluding very small and very large wetlands below 50 and above 500 ha still resulting in overall higher values in the former category substantiates this possible explanation (c.f. Fig. 10). This confirms that, in order to make complete ecosystem assessments, quantitative indicators need to be contextualized with local expert knowledge (Haase et al., 2018).

Management categories regulate how wetlands can be used. That does not mean that all allowed practices are actually applied. The comparison of WUI values across the Rwandan wetland management categories nevertheless shows that it can differentiate between wetland management systems. This insight may be used to monitor whether WUI value distributions are stable over time, shift up- or downward, or change their range within a management category. Depending on the type of change, shifts may signal that regulatory efforts are successfully implemented, or that further action is needed. Moreover, the presented method can be applied for the intercomparison of WUI values across regions to estimate the pressure on wetland ecosystems in other specific management categories, like Ramsar sites, habitat management areas, or agricultural growth corridors. Changes in wetland ecosystems are often determined through land use and land cover classification and change detection (e.g., Ballanti et al., 2017; Eid, 2020; Luvuno et al., 2016; Thonfeld et al., 2020a). Analyses through determination of changes that are more subtle and may therefore not directly lead to a change in land cover class are less frequent, but needed as these can nevertheless impact biophysical wetland functioning (Muro et al., 2018). WUI could add to the latter set of remote sensing based wetland monitoring approaches. The impact of land management on wetland health is complex, but reliable and continued spatial information on use intensity at the national to regional scale, as can be provided by the WUI layer, serves as an indicator of an important pressure, which can inform decision-makers and guide wetland managers to targeted interventions.

5.3. WUI for local-scale wetland health assessment

WUI can also contribute to wetland health assessment at the local scale, of which the WET-Health approach is an example that was already thoroughly tested in southern and East Africa, including field-based and remote sensing-supported modifications (c.f. Behn et al., 2018; Beuel et al., 2016; Dumakude and Graham, 2017; Kotze et al., 2012; Marambanyika et al., 2017). Marambanyika et al. (2017) acknowledge an

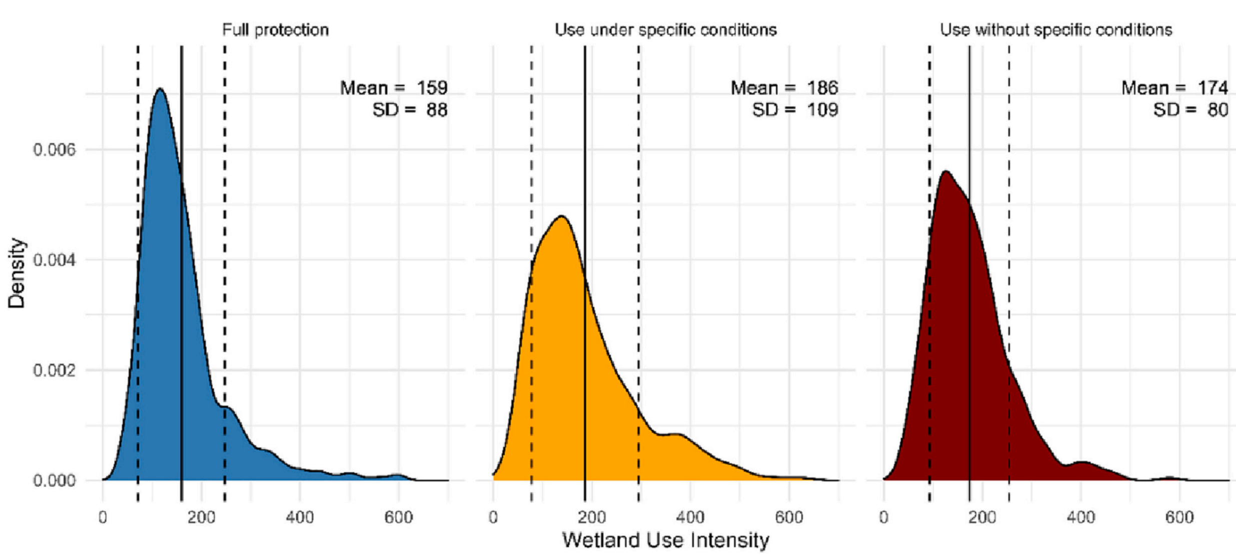

Fig. 10. Density plots of Wetland Use Intensity (WUI) value distribution within the wetland management categories protected, conditional use, and unrestricted use for wetlands between 50 and 500 ha size. Solid lines show the mean value for each category and dashed lines one standard deviation below and above the mean.

inherent subjectivity in the field-based assessment of the WET-Health modules through surveyors, and underline that remote sensing-based indicators such as WUI can add objectivity to wetland health assessments. Also, the newest version of the WET-Health approach relies more heavily on land surface data (Macfarlane et al., 2020), which has a high potential to integrate more remote sensing data. Yet, none of the listed studies has considered time series products including time series-derived data on use intensity.

WET-Health tries to reduce double-counting by assessing each of the modules hydrology, geomorphology, vegetation, and water quality separately (Beuel et al., 2016; Kotze et al., 2012). Nevertheless, when comparing the WET-Health module and average scores for patches of homogeneous land use within 250 × 250 m plots across Rwanda, the module scores are highly correlated. This is logical since impact scores in all modules are given according to specific land uses. Although the impact differs among modules, high environmental impact land uses usually entail high impact scores across all modules, although to a differing degree. Kotze et al. (2012) acknowledge these feedback effects between modules despite their separate assessment. This aspect of redundance could be interpreted as a strength of WET-Health, which makes the scoring more robust against outliers in any one of the categories. However, integrating different types and multiple sources of data can greatly enhance the performance of wetland assessments and monitoring systems (Beißler and Hack, 2019; Strauch et al., 2022). Thus, furthering the integration of remote sensing technology could add a dimension to field-based wetland health assessments that is complementary and not yet sufficiently exploited.

That WUI values are correlated with certain WET-Health modules and with the average score indicates that WUI is associated with the in-situ wetland health assessment. That the correlation is weak implies that the addition of a WUI-derived module may add information to the wetland health assessment that is verified to be related to wetland condition but not provided by the other modules. Such complementarity of meaningful data is generally desired when combining multiple indicators to measure environmental systems (Angermeier and Karr, 2019). In addition, WUI is not measurably influenced by the surface water regime and in contrast to the WET-Health assessment, it also does not directly depend on a specific land use class. This can be of interest in particular for agriculturally used land and for semi-natural vegetation, where WET-Health scores have a manifestly smaller range compared to WUI values.

Furthermore, WUI considers a time series instead of one point in time, which is an asset in wetland landscapes with both natural and anthropogenically induced dynamics (Guo et al., 2017; Mahdavi et al., 2018; Perennou et al., 2018). To estimate temporal dynamics to a certain degree, a surveyor would have to conduct multiple field visits or otherwise rely on information provided by locals, observation of signs of periodicity, and experience. In contrast, WUI can cover long time periods consistently and is temporally scalable. This can be of particular importance for Environmental Impact Assessments (EIA), which are conducted before any larger wetland development project in Rwanda and in other countries and ideally accompany them over an extended period (Aryampa et al., 2021; George et al., 2020; Heermans and Ikirezi, 2015; Nkundabose et al., 2020). They consider the effects of wetland development and intensification on aspects like water resources, soil and atmosphere, flora and fauna (Aryampa et al., 2021). Technical equipment, training, and transparency can be challenges to successfully conducting an EIA (George et al., 2020). The analysis provides evidence that WUI can serve as a broad standalone indicator that can be used to map the status and monitor the development of use intensity, and thus a critical driver of wetland health or ill-health. It could also be considered for integration into established field and remote sensing-based wetland health assessments like the WET-Health approach that can in turn factor into applied management elements, such as EIA. This adds a layer of spatially disaggregated, objective, reliable, geographically, and temporally scalable information to wetland monitoring and management.

5.4. Limitations

There are limitations to this study attributable to the analysis, to the data basis, and to the value of WUI in the management context. WUI is designed as a broad indicator that captures the spectral changes due to compound effects of different and interlinked land management practices and the sensitivity analysis of the relationship between land use class, WUI and SWD indicates that WUI is an independent data layer. But its informative value could only be inferred from the assumption that wetland use intensity is reflected in spectral changes over time, in combination with the statistical analyses. In contrast, a direct association with specific combinations of land management practices was not established and would require comprehensive spatio-temporal reference data of target combinations of management practices. Also, much finer wetland management e.g., to which degree management intensity is reflected for annual versus perennial crops like tea, which is characterized by continuous practices like plucking and pruning (Karuri, 2021), could not be discerned in this study. Although wetlands carrying both types of crops were sampled, the sample size did not suffice for a more detailed investigation.

Due to the length of the observation period, interannual differences are flattened out. To assess long-term baselines, longer input periods for the pseudo-year can be employed. But in general, the shortest input period possible should be used, since land use and land use intensity may change over time and would not be captured accurately. This period depends on cloud cover and on the number of available input images. Despite the frequent and extensive cloud cover over the study area, the two-year input period and bi-monthly composites provided adequate results, covered all seasons, and had a minimum of artifacts. However, in less cloudy areas it should be considered to reduce the maximum cloud coverage to obtain clearer imagery, reduce the composite timeframe to a month, or reduce the input period to a year. Evaluating the number of available input images and their cloud cover percentage for the periods in the time series help guiding these decisions.

The data used for reference and comparison are sources of analytical uncertainty. Both the time that part of WET-Health data was collected and the year the national wetland dataset was established do not correspond to the study period. However, reverting to historical data can be an advantage where current-year information is unavailable and can be turned into valid reference data, e.g., through spectral comparison or sample filtering (Lin et al., 2022; Maas et al., 2019; Muhammad et al., 2015; Padial-Iglesias et al., 2021). We present a way of reusing WET-Health data from 2013 for its application in the 2019–2021 period by evaluating spatial and spectral changes and discarding or updating incoherent reference polygons. Yet, there is inherent uncertainty that is propagated into the statistical results and that could not be quantified. For the national wetland management dataset, it can be assumed that the management framework remains in place from the time the respective order comes into force onwards. Therefore, this type of reference data does not expire until a new order is enacted. However, as an amendment was passed in 2017, the available spatial dataset had to be filtered, which introduces uncertainty. The selection of only the unchanged wetlands can bias the dataset towards the ones that are managed in a way that does not lead to the expansion nor to the reduction of wetland area. The accepted change of ±15% in area accounts for a certain range. Yet, this must be considered in the evaluation of the results' accuracy.

In the wetland management context, WUI, as a single information layer, cannot replace thorough investigations. To determine the type of wetland (e.g., Mandishona and Knight, 2022) or evaluate wetland user systems (e.g., Gebrekidan et al., 2020) and derive possible implications of changes in wetland use and use intensity, knowledge of the biophysical and socio-economic processes and interactions are needed to comprehensively understand their functioning. Further, specific aspects that threaten the ecosystem and wetland communities' livelihoods like water and soil pollution (De Troyer et al., 2016; Sekomo et al., 2011;

Uwimana et al., 2018a) cannot be derived directly with such a remote sensing product. However, we contend WUI can serve to rapidly assess cumulative use pressures on wetland health to spatially guide where such investigations should take place. It can be applied in addition to ground-based survey methods and contribute to often neglected follow-up studies on the environmental impact of wetland development efforts (George et al., 2020), in particular where resources are scarce.

6. Conclusions

The wetland health concept is closely tied to the idea of sustainable wetland use. It acknowledges the need to reconcile different land uses and maintain long-term wetland productivity to be able to meet the current and future need for food, water, and energy in East Africa. Wetland health assessments need to include a range of variables to be able to depict the condition and sustainability of use practices. Therefore, it would be a misjudgement to claim that established approaches should be completely replaced by remote sensing-based information. However, their contribution lies in the possibility of scalability, repeatability, and taking into account time series, since wetlands are characterized by seasonal, annual, and sometimes even decadal fluctuations. Meaningfulness and complementarity are important criteria that wetland health indicators need to meet. The presented WUI layer provides spatially consistent information on spectral changes on the wetland surface over time and is able to distinguish between different wetland management categories. It is linked to some existing field-based wetland health indicators, but only weakly associated with them, and thus does not duplicate information. WUI can be calculated in a fully automated manner, globally, in an open access processing environment, and with freely available data. This increases the applicability of the approach for long-term monitoring.

In Rwanda, regular agricultural surveys are conducted. These capture data on key agricultural indicators like inputs and yields, which can serve as determinants of agricultural use intensity. That means that consistent information on a key pressure on wetland ecosystems is already available, although it is not wetland specific and reported in a spatially aggregated form. In addition, remote sensing-based approaches like WUI provide spatially disaggregated location-specific and nuanced data on use intensity across land uses as a pressure that wetlands are subjected to. It can therefore complement wetland surveys at different scales, pinpoint clusters of high or low use intensity for management planning, and be incorporated in wetland health monitoring strategies, where the highest added value may exist in other East African regions with less frequent in-situ surveys, or generally in less accessible areas. As the Sentinel-2 image database grows, further research should explore the comparison of WUI between time steps to measure trends and shifts as well as across regions, other wetland management categories, and between specific agricultural use practices.

CRediT authorship contribution statement

Stefanie Steinbach: Conceptualization, Methodology, Investigation, Data curation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Esther Hentschel:** Investigation, Writing – review & editing. **Konrad Hentze:** Investigation, Writing – review & editing. **Andreas Rienow:** Supervision, Writing – review & editing. **Viviane Umulisa:** Writing – review & editing. **Sander J. Zwart:** Conceptualization, Methodology, Supervision, Writing – review & editing. **Andrew Nelson:** Conceptualization, Methodology, Resources, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the link to my code at the bottom of the paper.

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Appendix A. Supplementary data

The authors have shared the code and links to the Google Earth Engine (GEE) script in Appendix A of the paper. It can be found online at [https://doi.org/10.1016/j.ecoinf.2023.102032].

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