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Potential of Sentinel-1 Data for Spatially and Temporally High-Resolution Detection of Drought Affected Forest Stands

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Abstract: A timely and spatially high-resolution detection of drought-affected forest stands is important to assess and deal with the increasing risk of forest fires. In this paper, we present how multitemporal Sentinel-1 synthetic aperture radar (SAR) data can be used to detect drought-affected and fire-endangered forest stands in a spatially and temporally high resolution. Existing approaches for Sentinel-1 based drought detection currently do not allow to deal simultaneously with all disturbing influences of signal noise, topography and visibility geometry on the radar signal or do not produce pixel-based high-resolution drought detection maps of forest stands. Using a novel Sentinel-1 Radar Drought Index (RDI) based on temporal and spatial averaging strategies for speckle noise reduction, we present an efficient methodology to create a spatially explicit detection map of drought-affected forest stands for the year 2020 at the Donnersberg study area in Rhineland-Palatinate, Germany, keeping the Sentinel-1 maximum spatial resolution of 10 m × 10 m. The RDI showed significant ($p < 0.05$) drought influence for south, south-west and west-oriented slopes. Comparable spatial patterns of drought-affected forest stands are shown for the years 2018, 2019 and with a weaker intensity for 2021. In addition, the assessment for summer 2020 could also be reproduced with weekly repetition, but spatially coarser resolution and some limitations in the quality of the resulting maps. Nevertheless, the mean RDI values of temporally high-resolution drought detection maps are highly correlated ($R^2 = 0.9678$) with the increasing monthly mean temperatures in 2020. In summary, this study demonstrates that Sentinel-1 data can play an important role for the timely detection of drought-affected and fire-prone forest areas, since availability of observations does not depend on cloud cover or time of day.

Keywords: SAR; Sentinel-1; drought; forests; fire; radar



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1. Introduction

Dry periods, such as those that occurred during the three consecutive dry summers 2018, 2019 and 2020 have caused substantial damage to forests in Central Europe [1,2]. While in 2004–2009 total tree cover loss caused by wildfires worldwide was 24.5 Mha, it increased to 33.18 Mha in the period 2010–2015 and finally doubled in 2016–2021 to 49.6 Mha compared to 2004–2009 [3]. Over the period 2001–2021, 2016 showed the greatest tree cover loss due to forest fire globally with 9.61 Mha, which represented 32% of the total tree cover loss for that year [3]. The same trend is observable for temperate regions in Central Europe, which were not prone to forest fires. Referring to the Visible Infrared Imaging Radiometer Suite (VIIRS) active fire data published on Global Forest Watch, in the federal state of Rhineland-Palatinate, the number of forest active fire detections in the period 2018–2020 was significantly ($p = 0.0265$) higher than in the period 2012–2017 [4]. In 2020, a particularly high number of forest active fire detections, over 200, were reported [4].

To deal with this increased risk of forest fires, continuously recorded, spatially and temporally high-resolution wall-to-wall information about the condition of forest stands is required. Approaches to obtain this information from optical satellite data, such as Sentinel-2 imagery, have already been developed [5–7]. A major disadvantage of optical

data is the limited availability due to cloud cover [8]. In contrast, Synthetic Aperture Radar (SAR) systems such as Sentinel-1 (S-1) could have great potential to fill these monitoring gaps due to their all weather and night-time acquisition capabilities.

C-Band SAR data, such as imagery from S-1, are essentially influenced by the structural and physical properties of the canopy, i.e., by the water content of branches and leaves [9,10]. This influence on the signal depends mainly on the high correlation between the S-1 backscatter coefficient and the dielectric constant, which for vegetation is mainly determined by the plant water content [11]. Accordingly, SAR data have already been widely used to estimate aboveground biomass of forest stands [12–16].

Additionally, multitemporal SAR-data have been used for studying ecophysiological dynamics. For the broad-leaf crop maize, it was found that multitemporal S-1 data showed a high sensitivity for estimating the crop height and canopy coverage [17]. The potential of microwave indices, derived from S-1 data, for the estimation of vegetation water content has also been demonstrated [18]. It is possible to distinguish forested from non-forested areas with high accuracy (80%) using S-1 data [19]. Additionally, it has been shown that multitemporal C-band backscatter data have significant potential to supplement optical remote sensing data for ecological studies and mapping of mixed temperate forests phenology [20,21]. C-band radar data has equally demonstrated a high potential for detecting windthrow damage in affected areas within two weeks [22] and it has been shown that the use of backscatter coefficients from S-1 data can deliver meaningful information about drought stress on grasslands [23].

S-1 data has been already used in the frame of drought detection, e.g., to investigate the response of agricultural fields to drought in the Netherlands. Results showed a 1 to 2 dB reduction in backscatter values for agricultural fields during drought period in comparison to the reference period [24]. In this study, signal-noise reduction was achieved by spatial averaging over agricultural parcels, while due to the flat surface, topographic influences did not require any consideration in data preprocessing. S1 data were also successfully used in time-series analysis of a radar-optical change detection approach to detect drought impacts on vegetation [25] or to monitor the impact of drought on water bodies in object-based approaches [26,27].

However, these approaches are not suitable to generate a sufficient pixel-based signal noise reduction for the creation of high-resolution drought detection maps. In addition, the methodologies in the object-based approaches are not transferrable to pixel-based approaches, since the signal noise is not sufficiently reduced on pixel level.

Existing approaches for S1 based drought detection do not simultaneously consider all influences that cause variations in the backscattering signal (i.e., signal noise, topography and viewing geometry) which is important for the pixel-based high-resolution mapping of drought affected forest stands.

Therefore, we introduce a novel S-1 Radar Drought Index (RDI) in this paper, which enables dealing with all mentioned disturbing influences simultaneously in an efficient way. To assess fire risks, spatially comprehensive and temporally close information on affected forest areas is required. Thus, we present two different strategies of producing RDI maps on drought-affected and fire-endangered forest stands: Firstly, we test whether S-1 data can generally be used to provide meaningful results at a spatial resolution of $10\text{ m} \times 10\text{ m}$ representative for critical summer periods. Secondly, it is tested whether S-1 data can also be used to monitor progressing drought stress in forests at a temporally higher resolution (i.e., weekly) accepting a reduced spatial resolution of $30\text{ m} \times 30\text{ m}$ for signal noise reduction. Thus, the aim of this study is to test the hypothesis that S-1 backscatter coefficients are sufficiently sensitive to producing a meaningful assessment of drought-affected and fire-endangered forest areas within a developing drought year including the question whether it is possible to separate drought-affected forest stands from unaffected forest stands at high spatial resolution, despite the influence of speckle noise originated by the SARs system's coherent nature [28]. Therefore, an efficient reduction

of speckle noise is the prerequisite to map the relatively small signal changes in the S-1 data caused by the reduction in water content.

The paper is further divided into four sections below. First, in Section 2, the study area (Section 2.1), the study period (Section 2.1) and the used data (Section 2.2) are presented. Subsequently, the selected methods are described step by step (Section 2.3), beginning with the preprocessing of S-1 data, which also includes the consideration of unwanted data variations on the signal (Section 2.3.1), and finally leading to the calculation of the RDI (Section 2.3.2). At the end of Section 2, the selected methods for validating and analyzing the products are presented (Section 2.3.3). In Section 3, all results are presented, starting with the analysis of the speckle noise reduction performance (Section 3.1), followed by presentation of generated high-resolution drought detection maps (Section 3.2) and their comparison with soil moisture classes and topography indices (Section 3.3). The results are discussed in Section 4 and finally, a conclusion of the study follows in Section 5.

2. Materials and Methods

2.1. Study Area and Period of Investigation

To evaluate the potential of S-1 data for assessing the changing vitality of forest ecosystems, this paper analyzes an extreme drought-affected situation. Both the study area and period of investigation (as mentioned above, 2018–2021), were selected so that the vitality of forest stands very likely will be severely impaired by drought.

With more than 40% forest cover, the federal state of Rhineland-Palatinate (RLP), located in the southwestern part of Germany, is one of most densely wooded federal states [29]. The forest area around the Donnersberg (49.62° N, 7.92° E, see Figure 1) was chosen based on previous investigations [4,5], that showed that, in the Donnersberg area, forest stands which are severely affected by drought occur in close proximity to stands with good water availability that are more resistant to drought. Therefore, this area with very heterogeneous location properties is particularly suitable as an investigation area regarding the monitoring of climate change in forests of RLP. The study area covers about 25 km² in the relatively dry part of RLP and is entirely covered by forests. Main tree species with the highest proportions in the study area are European beech (*Fagus sylvatica* L.), Sessile oak (*Quercus petraea* (Mattuschka) Liebl.) and Pedunculate oak (*Quercus robur* L.), followed by Scots pine (*Pinus sylvestris* L.), sycamore maple (*Acer pseudoplatanus* L.), and Norway spruce (*Picea abies* (L.) H. Karst.). Soils in the Donnersberg-Rhyolith-Dome are developed on igneous, volcanic rock of silica-rich composition. Owing to the rugged topography with an altitude range of 350–687 m above sea level and slopes of varying orientation, soil depth and corresponding water storage capacities are highly variable and provide diverse growth conditions. Due to its geographical position on the leeward side of the Hunsrück mountain range, the area is prone to pronounced dry spells during spring and summer.

The years 2018, 2019 and 2020 had exceptionally low precipitation and at the same time high temperatures compared to the long-term average for the years 1991–2020 and were therefore chosen as the period of investigation. The mean annual temperature during this period was 10.8 °C–11.3 °C, which is 0.9 °C–1.4 °C more than the long-term average [30]. During the same time, precipitation amounts did not reach the long-term average for almost the whole of Rhineland-Palatinate (see Figure 2).

Furthermore, the year 2021 will be used as an example for climatic conditions which correspond better to the climatic long-term average regarding temperature [32] and precipitation in the study area [33].

In Figure 3, monthly precipitation sums and monthly mean temperature of 2018, 2019, 2020 and 2021 are compared to the long-term average (1969 to 2021) measured at Ruppertsecken, a weather station located close to the study area. In large parts of the vegetation period 2018, 2019, and 2020 temperatures were above the long-term average while less precipitation was registered, which indicates drier conditions in the vegetation period in these years.

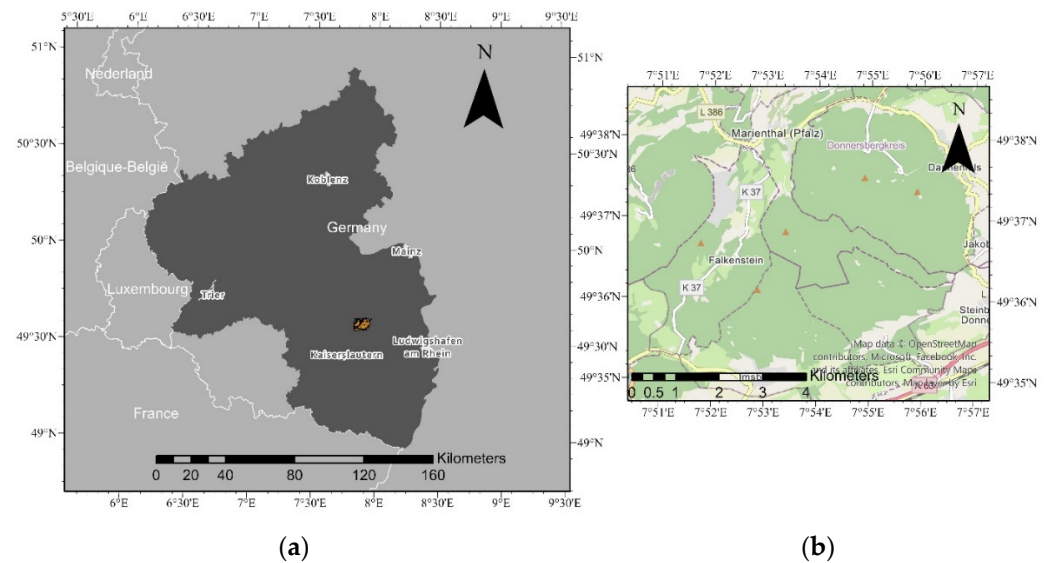


Figure 1. (a) Location of Donnersberg (orange) in Rhineland-Palatinate. (b) Area around the Donnersberg.

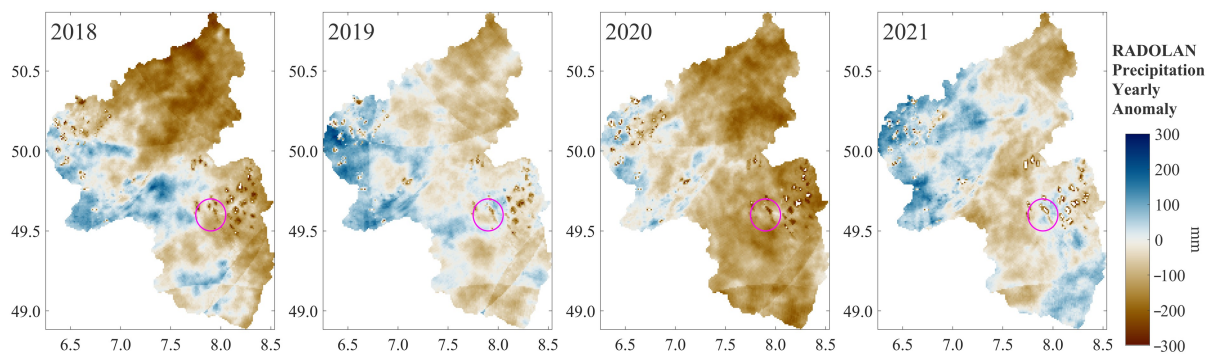


Figure 2. Precipitation Anomaly in RLP for the years 2018 to 2021 in comparison to the mean (2007 to 2021), the Donnersberg area is circled. Data source: German Weather Service DWD [31].

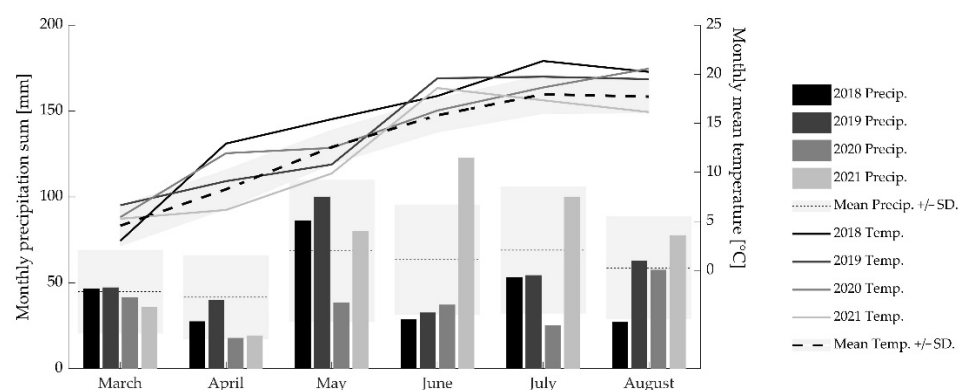


Figure 3. Meteorological data from the weather station Ruppertsecken from German Weather Service (DWD). Monthly sums of precipitation and mean temperatures for the vegetation periods in years 2018, 2019, 2020 and 2021 are shown in comparison to the long-term average (1969 to 2021).

2.2. Data

2.2.1. Sentinel-1

In this paper, S-1 C-band Interferometric Wide swath (IW) mode Ground Range Detected High Resolution (GRDH) images in both polarizations, VH and VV, were used [34]. The S-1 satellite system consists of two platforms (Sentinel-1A and Sentinel-1B), which

orbit the earth at an altitude of 693 km at 180° apart from each other. The 5.4 GHz frequency microwave pulses penetrate clouds, which is advantageous to provide a stable repetition of image acquisitions for a temporally high-resolution forest monitoring. C-Band SAR is mainly sensitive to water and objects containing water [35], which is suitable for calculating a radar drought index. The antenna measures the strength of the echo, which is backscattered from the forest canopy. The properties of the backscattered signal depend on frequency, polarization, incidence angle (the angle between the plane surface and the direction of radar illumination), the physical characteristics of the surface and objects on the ground (primarily structure and geometry), and the electromagnetic properties of those, namely the dielectric constant. The latter is highly sensitive to water content [36] which can be used as a proxy for drought stress.

For our study, only images recorded in ascending orbit were chosen. We also tested using images recorded exclusively in descending orbits. These showed comparable results, but speckle noise influence was stronger. The combined use of images of ascending and descending orbits did not improve the results meaningfully. Therefore, the use of images recorded in ascending orbits is considered as optimal in terms of processing effort (i.e., data amount and processing time) and quality of the results. In addition, this choice assures that the time series includes only images acquired at the same local time around 5:30 PM, whereby the recording conditions and external environmental influences at the location are as comparable as possible. The study area is covered by both S-1A and S-1B with incidence angles between approximately 36° and 44°. With respect to the proposed assessment concept, it is important to understand that we used data from two different observation positions of S-1A and S-1B, respectively, so that data from a total of four different observation characteristics were available. This results in a temporal resolution of four images in twelve days, which was considered adequate for the scope of this work. A total of 58 Sentinel-1 images were used. A total of 16 images acquired from 30 April to 23 June 2019 were used to calculate a reference composite representing normal conditions in spring 2019. Eight scenes each were used to calculate the observation composites from the drought influenced summer periods of 2018, 2019 and 2020, with acquisition dates from the end of July to the end of August. In 2020, additional ten scenes acquired between end of June and end of July were used for the calculation of temporally high-resolution drought detection maps.

C-band SAR backscatter is not only sensitive to the water content of observed objects, but also to surface moisture. Wetting of the vegetation after precipitation [37] or temperatures below freezing point [38] can lead to sudden changes in the signal, without a change in structural properties or vegetation water content. To account for that, the Radolan precipitation data (compiled from precipitation radar measurements) and station data from the German weather service DWD [39,40] were included in the analysis. They are available at daily or hourly intervals in a $1 \times 1 \text{ km}^2$ raster for the whole of Germany. In addition, station data from the Service Center of the Rural Area Rhineland-Palatinate was considered when selecting the S-1 imagery and interpreting the results [41].

2.2.2. Sentinel-2

In the wider framework of developing strategies for an exhaustive characterization of forest areas on federal state level (Rhineland-Palatinate), optical satellite systems are fundamental to understand the phenological dynamics throughout the different seasons. The Sentinel-2 (S-2) constellation provides a well-suited combination of spatial, temporal and spectral resolution for characterizing the annual phenological dynamics and associated variability of greening up and senescence of forest systems.

We used the complete volume of S-2 data which has been recorded over the federal state of Rhineland-Palatinate since the beginning of S-2-data-distribution in 2015. The complete S-2 data collection has been converted into an archive of analysis ready data (ARD) (<http://ceos.org/ard>, accessed on 22 November 2022) based on the open-source software FORCE (Framework for Operational Radiometric Correction for Environmental

monitoring) [42–44]. FORCE supports processing of all Landsat and the Sentinel-2 imagery and is capable of processing Level 1 products to Level 2–4 products, which represent different degrees of ARD [45]. To reduce the amount of redundant data between overlapping and neighboring orbits, FORCE adapts gridding on Level 2, i.e., all generated products are reprojected into one coordinate system (in our case ETRS89 Lambert Equal Area) and organized in tiles of $30 \times 30 \text{ km}^2$ (see Figure 4).

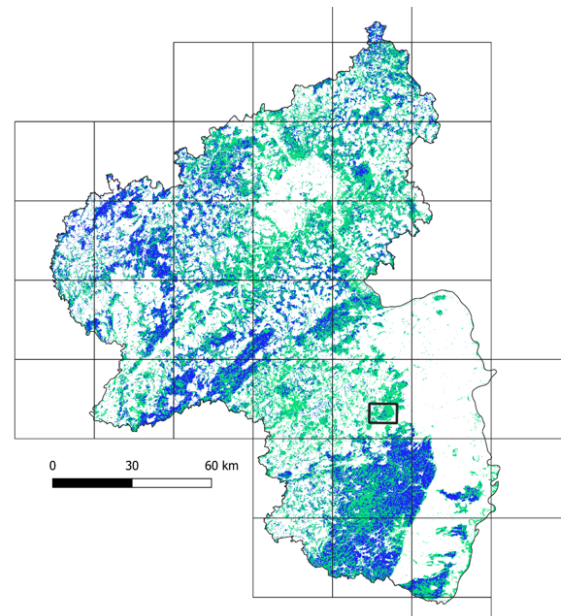


Figure 4. The S-2 analysis ready data collection (ARD) tile grid (ETRS89 Lambert Equal Area projection) for Rhineland-Palatinate, overlaid on total forest cover (2019) (<https://lvermgeo.rlp.de>, accessed on 22 November 2022); coniferous forest areas are shown in dark blue. The study area is marked by the black rectangle.

The S2-ARD archive used for this study provides easy access to re-projected, cloud-masked and atmospherically corrected S-2 data organized in 38 tiles for the time period from summer 2015 to October 2020.

2.2.3. Digital Elevation Model

Furthermore, a freely available digital elevation model [46] from the Copernicus program is used to calculate the aspect for the study area. The European Digital Elevation Model (EU-DEM), version 1.1 has been created by merging NASA’s SRTM-DEM with ASTER-GDEM data to generate a DEM with a weighted averaging approach [47]. Vertical accuracy ($\pm 7 \text{ m RMSE}$) of the product was improved by additional usage of ice, cloud and Land Elevation Satellite (ICESat) data [47]. EU-DEM v1.1 is provided with a spatial resolution of 25 m and was published in 2016 [46].

2.2.4. Forest Mask

A forest mask is also used, which is derived from the freely available Corine Land Classification 2018 (CLC2018) of the Copernicus program [48]. CLC2018 is produced by national teams based on classification of Sentinel-2 and Landsat-8 satellite imagery [48]. The resulting product in vector layer format is used for production of a forest mask covering the Donnersberg area.

2.2.5. Soil Moisture Classes

Finally, for evaluation of the results, a vector layer of soil moisture classes (SMCs), ranging from “extremely moist” to “extremely dry”, provided by the State Forest Administration as part of their site characterization, were included. This official digital site

classification map integrates information on soil depth, texture, bulk density, and soil organic matter with climatological factors and topographic site characteristics (slope, aspect) to provide a qualitative assessment of the soil water balance [49].

2.3. Radar Drought Index

The workflow to produce the RDI is presented in Figure 5. It consists of three main steps, data preprocessing (i.e., correction to gamma naught, spatial and temporal aggregation and the correction of systematic sensor variations), validation based on the elevation data derivatives aspect and slope and a soil classification map, as well as the thematic analysis (plausibility analysis of the map product compared to the validation input). All processing steps are described in detail in the next sections.

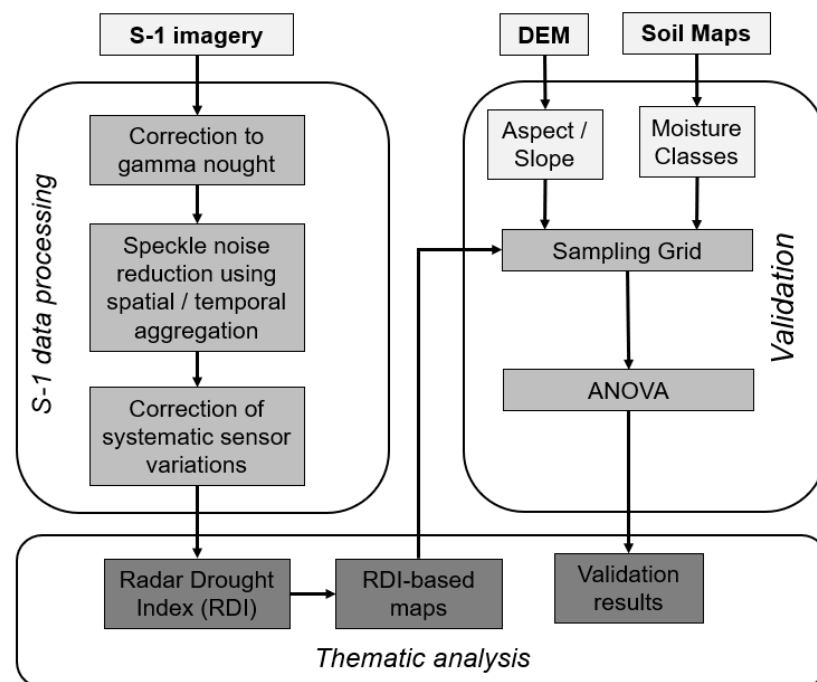


Figure 5. Schematic description of the workflow for the RDI calculation and validation.

2.3.1. S-1 Data Processing

All processing steps, shown in Figure 6, were performed using the “Sentinel Application Platform SNAP” [50], based on the state-of-the-art standard preprocessing workflows for Sentinel-1 data [51].

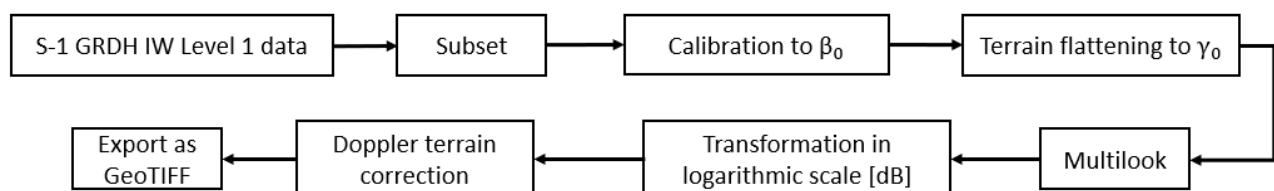


Figure 6. Sentinel-1 preprocessing workflow.

After importing the original data (Sentinel-1 GRDH IW Level 1 data), a spatial subset of the study area extent is processed using suitable corner coordinates. In the next two steps, the data gets radiometrically corrected to gamma naught [52]. This alternative to the common calibration to sigma naught [53] additionally takes the effect of topographic variation into account, which is very important regarding the partially rugged terrain in the study area and forested areas in the German mountain ranges in general. The consideration of terrain effects in the radiometric calibration is essential for further thematic

processing and analysis, i.e., the calculation of a consistent radar drought index over the whole study area.

The main limiting factor in the use of a SAR system is speckle, the signal noise due to SAR's coherent nature [28]. Speckle effects can hamper the quality and interpretability of SAR images. Several adaptive speckle filters that aim at reducing image noise while preserving edges exist, e.g., the Lee [54], enhanced Lee [55], or the Kuan [56] filters. All these filters estimate noise from local image statistics. However, for our temporal assessment strategy, these filters were not deemed optimal since image statistics might be different for the reference composite and the drought-affected composite. Thus, we chose to reduce noise solely by averaging: radar backscatter values can be spatially averaged over neighboring pixels, along temporal sequences, or a combination of both.

In order to obtain a spatially maximum high-resolution result, the initial pixel size of the Sentinel-1 images of 10 by 10 m was maintained. The signal noise was minimized solely by multi temporal averaging using image composites. A composite of $n = 8$ S-1 images was calculated for each summer in the investigation period (2018–2021) and a composite of $n = 16$ S-1 images for spring 2019. For n averaged images, the theoretical reduction of the signal noise is assumed by the factor $\sqrt{n}$ [57].

Alternatively, for obtaining a temporally high-resolution result, the reduction in signal noise was achieved by temporal averaging of only two images and additionally by averaging over neighboring image pixels, which is equivalent to a reduction in spatial resolution. Using the multilook operator in SNAP, the pixel size was reduced from 10 m $\times$ 10 m to 20 m $\times$ 20 m and 30 m $\times$ 30 m, which results in a reduction of speckle noise.

This multilook operator reduces speckle noise by combining several images, produced by space-domain averaging of a single look image, incoherently as if they corresponded to different looks of the same scene.

Next the data are transformed from a linear scale to a logarithmic scale. Since raw SAR data spans multiple orders of magnitude, a logarithmic transformation is a common way to transfer the data into a value range that is easier to handle and to visualize. Finally, a Doppler terrain correction is performed. Here, the pixels are projected to a common coordinate system and geometrical distortions eliminated by using a suitable digital elevation model.

In order to produce meaningful Radar Drought Index scores, data variations on the signal that are not related to canopy moisture variations but depend on systematic sensor variations must be identified and eliminated.

Most importantly, the systematic influence of viewing geometry on the signal must be considered. In general, the observation geometry of a satellite is characterized by the vertical incidence angle θ (the angle between incoming radiation and a normal to the earth's surface) and the horizontal azimuth angle ϕ (see Figure 7). The influence of the azimuth angle [58] is not considered here because only ascending orbits with constant azimuth angles were used (see Section 2.2.1).

In our study, we used observations from two orbital tracks with different incidence angles (see Section 2.2). Therefore, we analyzed whether the influence of the incidence angle is too large for a meaningful evaluation of the impact of canopy moisture content on the signal, which is expected to be less than one decibel [59]. Figure 8a shows how the mean backscatter values of the radar signals over all forest areas in our study are influenced by the different mean angles of incidence. To ensure comparable crown/canopy conditions, only S-1 images taken later than one day after precipitation events (identified from weather data [41]) were included in the analysis.

With up to 0.8 decibels, the influence of the incidence angle on the mean backscatter value of the radar signal over all forests areas in the study area is of a similar magnitude as the seasonal differences within the growing season. Thus, this influence must be eliminated by efficient processing strategies.

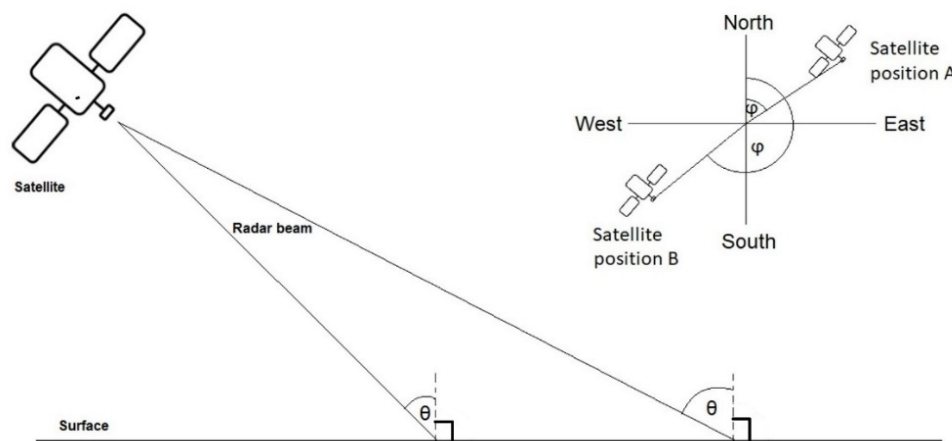


Figure 7. Illustration of vertical incident angle θ and the horizontal azimuth angle ϕ .

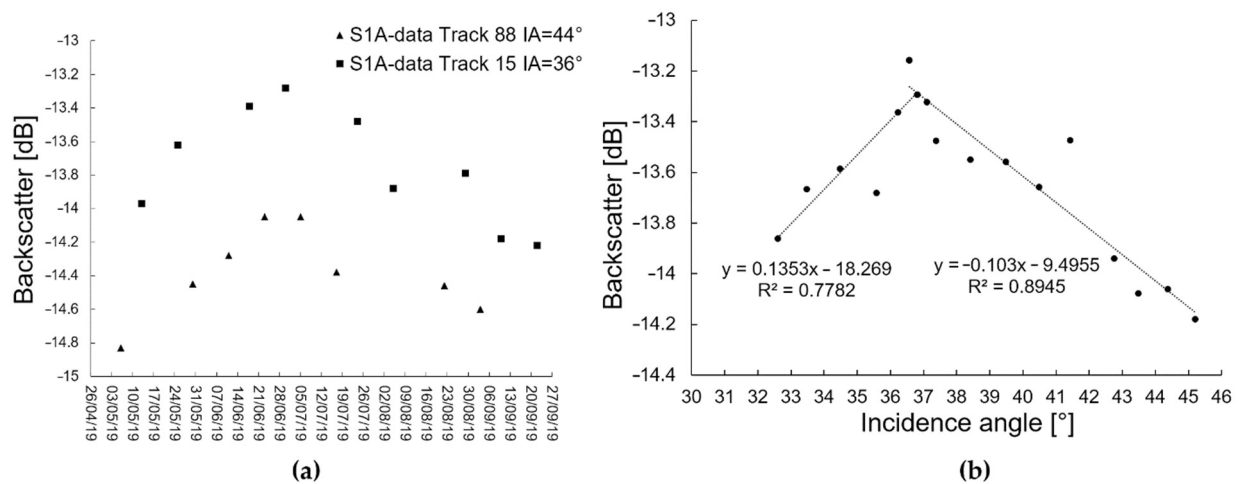


Figure 8. (a) Influence of different incidence angles (IA) on the average Sentinel-1 radar backscatter values over all forested areas; (b) Linear estimation of relation between mean radar backscatter values and incident angle over all forested areas.

One option is to normalize each scene to a common angle of incidence using linear estimates of the signal deviations as a function of the different incidence angles (see Figure 8b). Such a normalization of the data is common practice in scientific studies [58,60]. However, this purely data-based approach of normalizing to a common incidence angle of, e.g., 37° (see Figure 8b) is arbitrary and cannot be generalized. In addition, such a normalization needs a large amount of processing time for larger study areas and the use of imagery from more different viewing geometries than in this study. Signal levels must not only be analyzed with respect to the particular viewing geometry, but also separately for the S1A and S1B platforms. This should be avoided so that the presented methodology can also be transferred to larger areas without significant additional effort. Therefore, instead of normalization, the influences of different incidence angles are excluded during the calculation of RDI in a more straightforward way (see Section 2.3.2).

Another type of data variations, which are not related to canopy moisture variations, can arise by external environmental influences such as precipitation events. Signal variations might arise from precipitation events immediately before or during image acquisition. The intercepted water in the tree crowns plays an important, but undesired role in modifying the radar signal [61–63]. In the preprocessing workflow, this potential disturbance influence was avoided by excluding such scenes that were recorded within a day after a significant rainfall event (>10 mm) based on the available meteorological data [41].

2.3.2. Thematic Analysis

The definition of our SAR-derived index related to forest drought is based on the comparison between two different temporal compositing periods: a reference period characterized by maximum crown development not limited by water shortage or excessive temperatures and in comparison, one or more appropriate assessment periods within progressing drought phases.

The identification of the optimum reference period was based on evaluating the analysis-ready S-2 data archive (described in Section 2.2.2) for the period from 2015 to 2020 [5,45]. Because coniferous stands experienced excessive disturbance effects through bark beetle calamities since 2018, this analysis was limited to deciduous forest. Suitable spectral vegetation indices, such as the RCHLI [64], depend not only on leaf area index (biomass) but also chlorophyll.

$$\text{RCHLI} = \frac{\rho_{\text{NIR}}}{\rho_{\text{RedEdge}}} - 1 \quad (1)$$

This index (see Equation (1)) can be conveniently derived from the S-2 spectral band set and provides an excellent representation of annual phenological dynamics (see Figure 9). The considerable vertical spread of the data points, particularly between late June and early September, is an expression of the diverse growth conditions developed across temperature and rainfall gradients in Rhineland-Palatinate. Independently from the individual year, maximum leaf development is commonly reached in the second half of June (DoY 175–190), while stand chlorophyll concentration starts to decrease from early July onwards (see Figure 9). Depending on different weather conditions in the respective years, this phase is highly variable. In comparison to rapidly collapsing RCHLI scores in July/August (the consequence of heat waves and dry spells during the summers of 2018–2020), positive anomalies also may occur (for example, owing to a higher water availability due to rainfall above average in late August 2017).

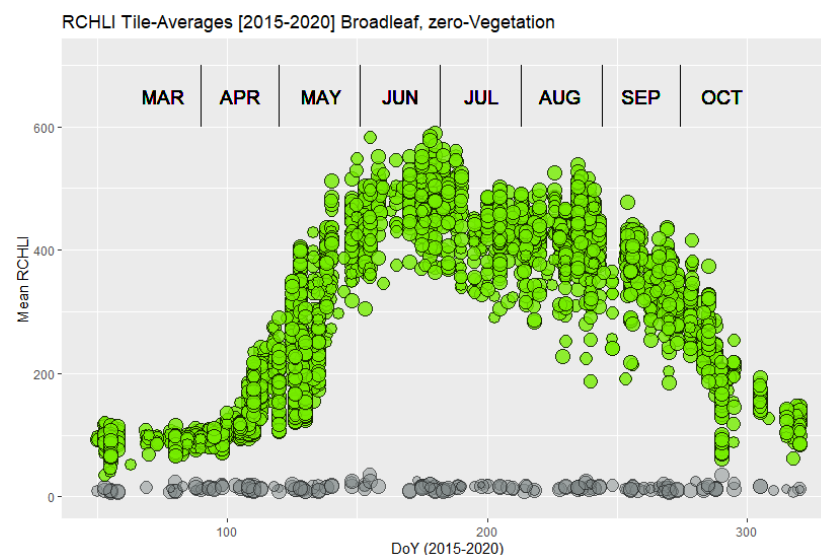


Figure 9. Average annual course of chlorophyll pigment concentration and biomass (RCHLI) of deciduous forest stands derived from S-2 imagery over the years 2015–2020. Each symbol corresponds to the RCHLI average for deciduous forest within each of the 38 S-2 tiles ($30 \times 30 \text{ km}^2$) with less than 25% cloud coverage of the tile area. For comparison, RCHLI values from unvegetated reference areas (airport aprons) are shown in grey.

The vitality peak in late June is expected to be usually not affected by water shortages, since soil water reserves from the winter can be used and the hot summer months have

not yet started. Scenes from this period are therefore suitable to create the pre-drought reference composite.

Depending on the individual onset of heat and drought phases in the following months, scenes from July to September are used to compile suitable observation composites.

Finally, the Radar Drought Index (RDI) is formed as a simple quotient of observation and reference composite.

$$\text{Radar Drought Index (RDI)} = \frac{\text{observation composite}}{\text{reference composite}} \quad (2)$$

During the summer months, variations of roughness characteristics in forest canopies are limited unless they are affected by management interventions, such as thinning and timber harvesting operations. Beside these local phenomena, the radar signal of a forest canopy is mainly driven by changes of di-electric properties of the crown layer, i.e., leaf water concentration. Consequently, reduced canopy moisture conditions produce increasing backscatter values in the corresponding observation composite and RDI scores. Increasing canopy moisture conditions, as they occur because of summerly rainfall events, lead to decreasing RDI scores.

To account for the systematic influence of viewing geometry on the signal (see Section 2.3.1), each composite used for the RDI calculation is composed of the same proportion of images of each observation characteristic. For example, if the reference composite (denominator, see Equation (2)) consists of a given percentage of images with one of the four different available observation characteristics, the observation composite (nominator, see Equation (2)) must be constructed with the same proportion of images with these observation characteristics. This way of considering systematic influences of viewing geometry is both simple and efficient. In addition to the fast integration of data from a wide variety of recording geometries, a further advantage of this method is that both polarizations, VH and VV, which are available with the S-1 data, can be used at the same time for building the comparable composites. This doubles the amount of data available, which significantly contributes to a successful noise reduction.

Table 1 provides an overview of the scenes that meet the selection criteria described above for creating comparable image compositions. Due to the different objectives, different scenes must be selected to produce spatially high-resolution RDI maps than to produce temporally high-resolution RDI maps. Despite the selection criteria used, enough S-1 images remain to form all the required composites required to evaluate the drought situation in the summers of 2018 to 2021. The reference composite is calculated using S-1 scenes from Spring 2019. This period was chosen since, in contrast to spring 2018, no S-1 image had to be excluded due to non-treatable image errors (image distortions or error values). Springs of 2020 and 2021 were not considered to minimize possible follow-up effects of the drought-affected previous years on the reference period.

As a basis for RDI, the observation composite and the reference composite must be calculated. To calculate the reference composite for the spatially high-resolution drought detection map, a total of sixteen preprocessed (see Section 2.3.1) S-1 images with 10 m × 10 m pixel size from spring 2019 are temporally averaged (Table 1 lists the acquisition dates of the used S-1 images, marked in different colors according to the different viewing characteristics). Thus, the calculated reference composite is in equal parts based on data from each of the four different viewing characteristics. To achieve consistency in the data, the observation composite must also be built up in equal parts from the four viewing characteristics, too. For each summer evaluation, eight scenes are used. Since these contain two images from each viewing geometry, both composites have a comparable structure and the influence of different characteristics is closed out by calculating the RDI (see Equation (2)). At the same time, signal noise is reduced by compositing. The terrain flattening carried out in the pre-processing of the data (see Section 2.3.1) excludes the influence of topographic variability in the study area.

Table 1. Overview of all Sentinel-1 imagery used. Dates of used S-1 datasets are colored according to the four different viewing geometries.

Overall Goal	Composite	Period	Selected S-1 Images			
Spatially high-resolution RDI map	Reference composite	Spring 2019	S1A Dates (rel. Orbit 15):	2019-05-01 2019-05-25	2019-05-13 2019-06-18	
			S1A Dates (rel. Orbit 88):	2019-05-06 2019-05-30	2019-05-18 2019-06-23	
			S1B Dates (rel. Orbit 15):	2019-05-07 2019-05-31	2019-05-19 2019-06-12	
			S1B Dates (rel. Orbit 88):	2019-04-30 2019-05-24	2019-05-12 2019-06-17	
		Summer 2018	S1A Dates (rel. Orbit 15):	2018-07-29	2018-08-22	
			S1A Dates (rel. Orbit 88):	2018-07-10	2018-08-15	
			S1B Dates (rel. Orbit 15):	2018-07-11	2018-08-16	
			S1B Dates (rel. Orbit 88):	2018-07-28	2018-08-21	
	Observation composites	Summer 2019	S1A Dates (rel. Orbit 15):	2019-07-24	2019-08-29	
			S1A Dates (rel. Orbit 88):	2019-07-17	2019-08-22	
			S1B Dates (rel. Orbit 15):	2019-07-18	2019-07-30	
			S1B Dates (rel. Orbit 88):	2019-07-23	2019-08-28	
		Summer 2020	S1A Dates (rel. Orbit 15):	2020-07-30	2020-08-11	
			S1A Dates (rel. Orbit 88):	2020-07-23	2020-08-04	
			S1B Dates (rel. Orbit 15):	2020-07-24	2020-08-05	
			S1B Dates (rel. Orbit 88):	2020-07-29	2020-08-10	
		Summer 2021	S1A Dates (rel. Orbit 15):	2021-07-25	2021-08-06	
			S1A Dates (rel. Orbit 88):	2021-07-30	2021-08-11	
			S1B Dates (rel. Orbit 15):	2021-07-31	2021-08-12	
			S1B Dates (rel. Orbit 88):	2021-07-24	2021-08-05	
Temporally high-resolution RDI map	Reference composites	Spring 2019	S1A Dates (rel. Orbit 15):	2019-05-01 2019-05-25	2019-05-13 2019-06-18	
			S1A Dates (rel. Orbit 88):	2019-05-06 2019-05-30	2019-05-18 2019-06-23	
			S1B Dates (rel. Orbit 15):	2019-05-07 2019-05-31	2019-05-19 2019-06-12	
			S1B Dates (rel. Orbit 88):	2019-04-30 2019-05-24	2019-05-12 2019-06-17	
	Observation composites (pairs)	Summer 2020	Pairs ($1 \times$ rel. Orbit 88 & $1 \times$ rel. Orbit 15)			
			2020-06-17 & 2020-06-24	2020-06-29	2020-06-30	
			2020-07-05 & 2020-07-06	2020-07-11	2020-07-12	
			2020-07-17 & 2020-07-18	2020-07-23	2020-07-24	
			2020-07-29 & 2020-07-30	2020-08-04	2020-08-05	
			2020-08-10 & 2020-08-11			

Contrary to the example shown before, the observation composite for the temporally high-resolution drought detection map is calculated by averaging only two scenes in order to enable a high temporal resolution. For this purpose, spatial aggregation is used for speckle noise reduction, resulting in a spatial resolution of $30 \text{ m} \times 30 \text{ m}$. The observation composites consist of two S-1 images, e.g., from July 5 and 6 July 2020, and the yellow and green marks in Table 1 indicate the different viewing characteristics. In order to keep observation and reference data characteristics consistent, the reference composite is created using eight scenes, which have the same data characteristics (marked in green and yellow). Thus, both composites are based on 50% of the two used viewing geometries and are used to calculate the RDI (see Equation (2)).

2.3.3. Validation

In the absence of specific terrestrial sampling data which are impossible to collect with adequate spatial density and distribution under the difficult terrain conditions in the study area, validation of the produced drought maps was only feasible with reference to existing geodata layers.

As a first validation layer for the spatially high-resolution RDI maps, we used an aspect map derived from digital elevation data (see Section 2.2.3). Under the assumption that drought stress results from the coincidence of absence of rainfall and high temperatures it is expected that southerly exposed slope areas (SE to SW) are prone to be more severely affected being exposed to excess solar irradiance. In the study area, such conditions are exemplary developed due to the predominantly NW-SE oriented valley and ridge sequences.

This, however, to some extent neglects the modifying impact of spatially variable soil conditions. To include these effects in the validation, we included the official digital site classification map (provided by the State Forest Administration) in the analysis (see Section 2.2.5). This information layer builds on a long tradition in establishing maps of forest site conditions, and it integrates information on soil depth, texture, bulk density, and soil organic matter with climatological factors and topographic site characteristics (aspect) to provide a qualitative assessment of the soil water balance [49]. The map displays a series of soil moisture classes (SMCs) (“Frischestufen”), ranging from “extremely moist” to “extremely dry”. The SMCs with a high risk of drying out are mostly located on shallow soils, primarily found on isolated mountain tops, ridges and on sloping terrain (primarily with southerly orientation), while the more favorable locations with sufficient long-term water supply are rather located on plateau areas, lower slopes areas and in valley bottoms [6].

Soil moisture classes (SMC) 1–4, which represent drier site conditions, can be expected to have significantly higher RDI values than the higher soil moisture classes (5–9). Similarly, sun-exposed slopes (south to southwest) should have higher RDI values than northerly exposed slopes.

To test these hypotheses, all data, index values, aspect values and soil moisture classes, were sampled using a randomly distributed grid of points ($n = 1000$) which covers the whole study area. To minimize spatial autocorrelation, the random points were placed at least twice the pixel length (20 m) apart from each other. The relatively large number of validation points was chosen with respect to the substantial variability in the backscatter values of the Sentinel-1 data, which is caused by the signal noise. Afterwards, an analysis of variance (ANOVA) is calculated first with the aspect and second with soil moisture classes as independent variable and the radar change index values as dependent variable.

3. Results

3.1. Speckle Noise Reduction

The efficient reduction of the signal noise plays a central role for the quality of the results. Figure 10a shows how the standard deviation of the temporally high-resolution RDI maps, which are largely determined by signal noise, are reduced by averaging over multiple temporal images. Figure 10b shows the same for spatially high-resolution RDI maps by reducing the spatial resolution.

Figure 10 demonstrates that a reduction in speckle noise by averaging multiple images is compliant with the theoretically expected behavior, although the standard deviation is not only caused by noise, but also the variation of surface conditions over space and time (tree densities, tree species, phenology, weather conditions). With increasing number of S-1 images used for averaging, the effect of reducing the signal noise saturates. Using more than eight scenes from May 2019 (see Table 1) for the multitemporal averaging shows no further decrease of noise.

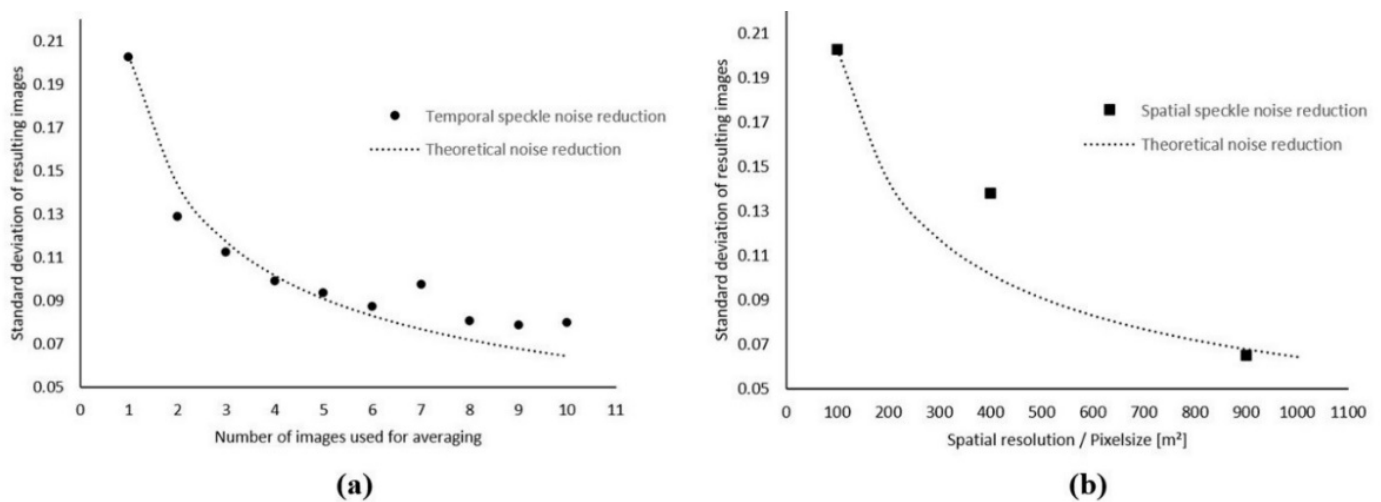


Figure 10. (a) Performance of speckle noise reduction by averaging over multiple temporal images compared with the theoretical noise reduction (factor $\sqrt{n}$). (b) Performance of speckle noise reduction by reducing of spatial resolution compared with the theoretical noise reduction (factor $\sqrt{n}$).

In the second part of the study, temporal aggregation was replaced by speckle reduction at the expense of a decreased spatial resolution. The reduction in the spatial resolution from $10 \text{ m} \times 10 \text{ m}$ to $30 \text{ m} \times 30 \text{ m}$ corresponds to an averaging over nine neighboring pixels from the original resolution. Additionally, in this case the achieved results correspond to the theoretically expected results of noise reduction.

3.2. Radar Drought Index

Firstly, it was analyzed whether it is possible to separate drought-stressed forest stands from less or non-affected forest stands using SAR C-band data at a spatial resolution of 10 m by 10 m .

Figure 11 shows the spatially high-resolution RDI maps for the four study years. For 2018, some strongly affected areas are visible. For 2019, only small areas appear affected by drought, spatially consistent patterns are hardly discernible. In 2020, however, clearly recognizable spatial patterns of drought-affected areas have developed. For 2021, the spatial pattern of stands affected by drought are again weaker, but still similar to the situation of 2019, which indicates follow-up effects from the previous year.

To support the interpretation of these spatially high-resolution RDI maps, Figure 3 shows meteorological data from the weather station Ruppertsecken of German weather service (DWD), which is located close to the study area. The precipitation amounts for April, May and July 2019 were higher than in 2018 and 2020. This explains why strongly drought-affected areas are not visible in the radar data in 2019, but in 2018 and 2020. In 2020, precipitation amounts were very low, which explains the strong impact of drought shown in the radar drought index. A further likely reason is that 2020 was already the third year with significantly less precipitation and higher temperatures after 2018 and 2019 and also the winter months between the years tended to be low in precipitation. Therefore, the precipitation deficit of the previous years could have an effect on 2020. A similar drought-related pattern is visible in the map of 2021, but the intensity is less compared to the year 2020. It should be related to the fact that concerning temperature and precipitation the year 2021 can be seen as statistically quite average, which might have helped the vegetation to mostly recover with the exception of the particularly strong affected forest areas.

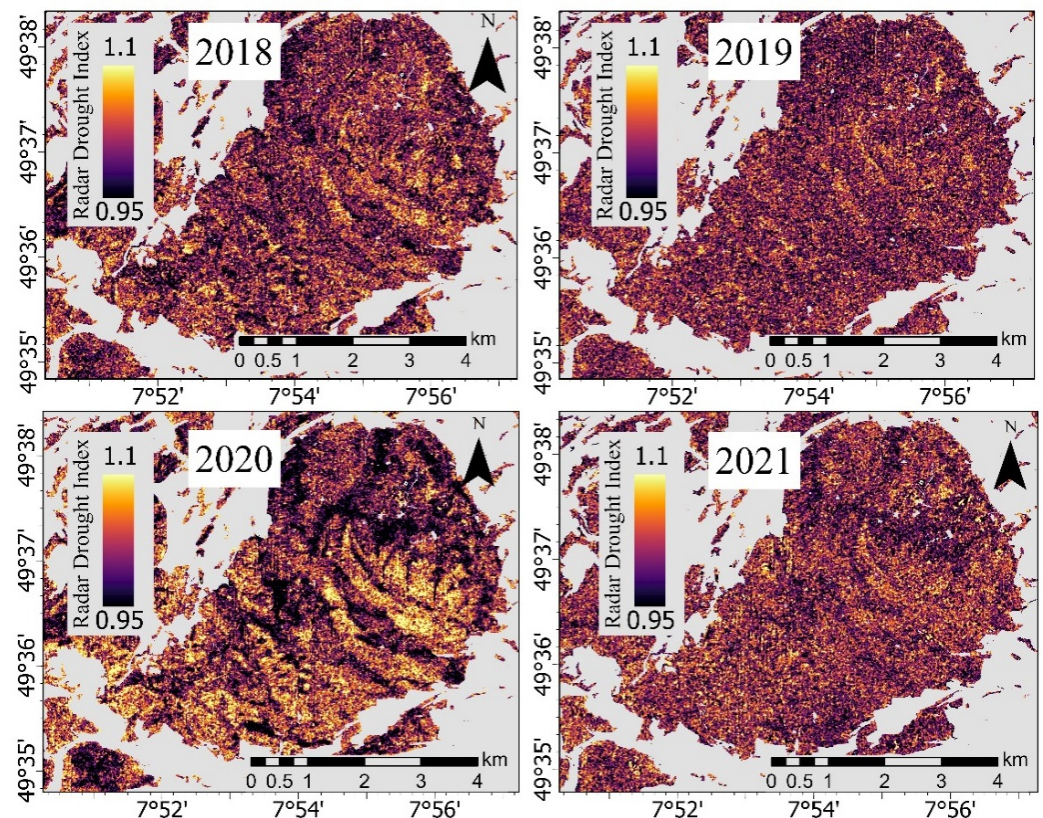


Figure 11. Spatially high-resolution maps of 2018, 2019, 2020 and 2021 for forest stands at the Donnersberg area.

With respect to the second objective, it was important to understand whether S-1 SAR data can provide a meaningful, temporally high-resolution representation of the development of the drought stress influence in forests within one specific drought summer. For this analysis, the spatial resolution of the S-1 data was reduced to $30\text{ m} \times 30\text{ m}$ (see Section 2.3.1).

The objective here was to identify spatial patterns of increasingly drought-affected forest stands based on a sequence of S-1 images, which would be of utmost importance to use S1-imagery for continuously updating fire risk products.

Figure 12 shows temporally high-resolution RDI maps in the Donnersberg area for the period from end of June 2020 to mid-August 2020. At the beginning (mid-June) hardly any spatial patterns related to drought stress are visible. Progressing in time, however, the RDI is generally increasing, but also the spatial patterns of excessively affected areas are increasingly more pronounced. This development could be expected since the region faced excessively dry and hot conditions without any significant precipitation events in the period shown.

Figure 13 shows RDI values spatially averaged over the temporally high-resolution maps (see Figure 12), compared to precipitation and temperature averages of the previous 30 days. A strong correlation ($R^2 = 0.9678$) between mean RDI values and monthly mean temperatures is observed. Thus, the rising trend of temperature in the study area is reflected very well by rising RDI values during the summer period 2020. The relationship between the mean monthly precipitation and mean RDI values are weaker ($R^2 = 0.5091$).

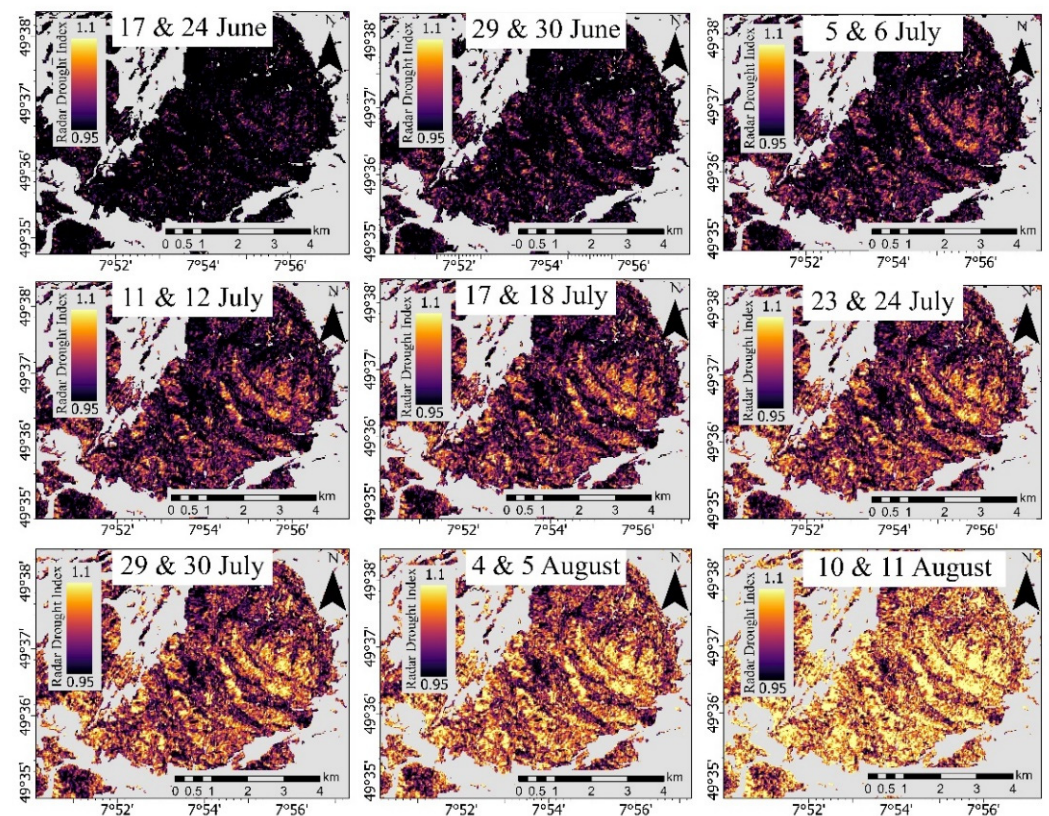


Figure 12. Temporal development of the RDI in the Donnersberg region for the period from the end of June 2020 to mid-August 2020.

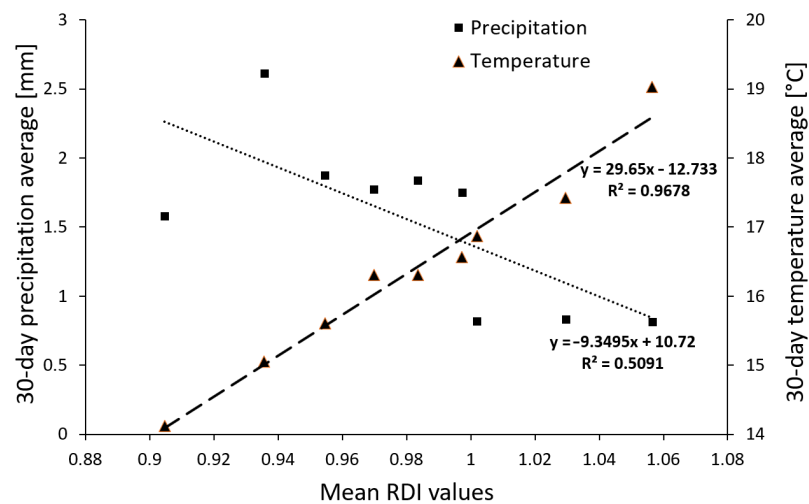


Figure 13. Correlation between mean RDI values of high temporally resolution maps and 30-day precipitation and temperature average calculated using meteorological data [41] for the area of the Donnersberg.

3.3. Comparison to Soil Moisture Classes and Topographic Indices

The visual examination of the RDI products is fully supported by a quantitative analysis. Both the relationship between the high spatial resolution result from summer 2020 and aspect and the soil moisture classes were statistically analyzed (Figure 14).

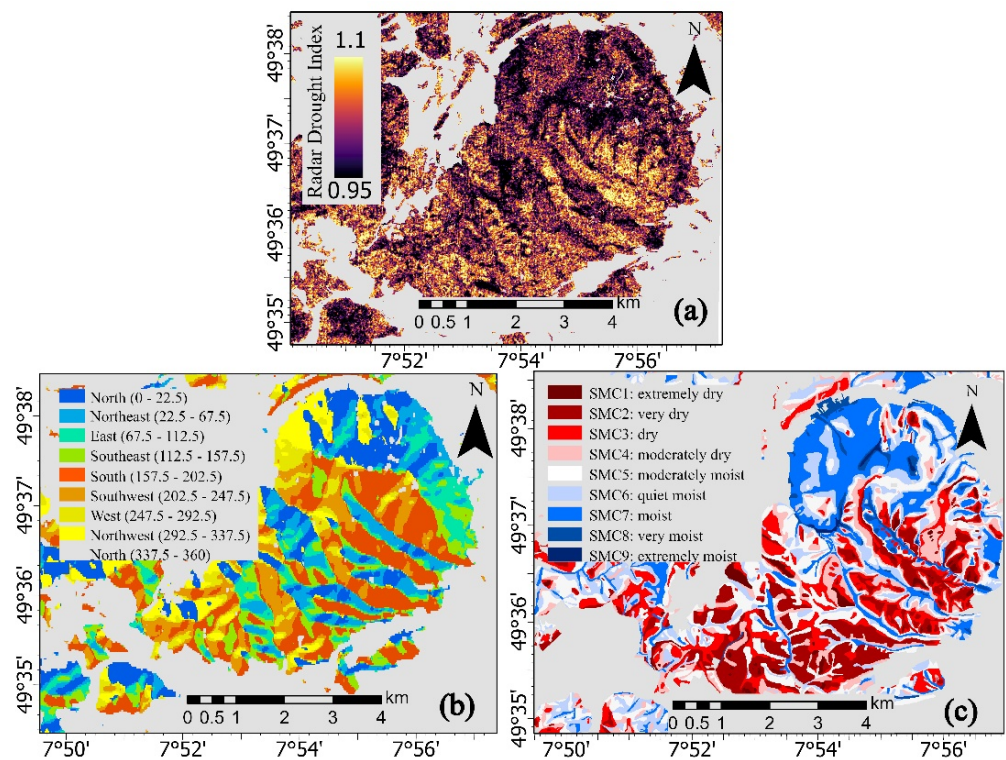


Figure 14. Comparison between (a) Spatially high-resolution RDI map for 2020, (b) Aspect and (c) Soil moisture classes at the Donnersberg area.

The results of the aspect analysis are presented in Table 2 and Figure 15. The values of the RDI for south, south-west and west oriented slopes are significantly higher than for east, north, north-west or north-east oriented slopes. The spatially high-resolution RDI map for 2020 thus has a statistically significant informative value for drought-stressed forest stands around the Donnersberg.

Table 2. Results of ANOVA. Left of diagonal: *p*-Values (in italics). Right of diagonal: Differences of Radar Drought Index depending on aspect (in bold). Significance levels: * ($p \leq 0.05$), ** ($p \leq 0.01$), *** ($p \leq 0.001$).

	North	Northeast	East	Southeast	South	Southwest	West	Northwest
North	x	0.009	0.014	0.023	0.046 ***	0.059 ***	0.049 ***	0.007
Northeast	<i>0.93</i>	x	0.004	0.014	0.037 ***	0.052 ***	0.040 ***	0.002
East	<i>0.70</i>	<i>0.99</i>	x	0.009	0.032 **	0.045 ***	0.035 **	0.007
Southeast	<i>0.06</i>	<i>0.72</i>	<i>0.97</i>	x	0.023 *	0.036 ***	0.026	0.016
South	<i><0.001</i>	<i><0.001</i>	<i>0.001</i>	<i>0.03</i>	x	0.013	0.003	0.040 ***
Southwest	<i><0.001</i>	<i><0.001</i>	<i><0.001</i>	<i><0.001</i>	<i>0.62</i>	x	0.009	0.052 ***
West	<i><0.001</i>	<i><0.001</i>	<i>0.007</i>	<i>0.09</i>	<i>0.99</i>	<i>0.96</i>	x	0.042 ***
Northwest	<i>0.99</i>	<i>0.99</i>	<i>0.99</i>	<i>0.54</i>	<i><0.001</i>	<i><0.001</i>	<i><0.001</i>	x

The results of the soil moisture class analysis are summarized in Table 3 and Figure 16. It becomes apparent that the RDI values for soil moisture classes 1 (extremely dry), 2 (very dry) and 3 (dry) are significantly higher than for soil moisture classes 5 (moderately moist), 6 (quite moist) and 7 (moist). Since they rarely occur in the study area, the soil moisture classes 8 (very moist) and 9 (extremely moist) only play a subordinate role in the analysis.

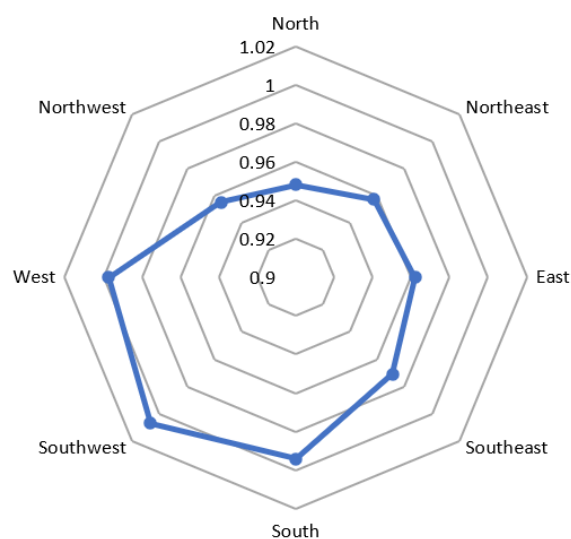


Figure 15. Spider web diagram showing a correspondence of higher mean RDI values for southerly oriented areas.

Table 3. Results of ANOVA. Left of diagonal: *p*-Values (in italics). Right of diagonal: Differences of Radar Drought Index depending on soil moisture classes (in bold). Significance levels: ** ($p \leq 0.01$), *** ($p \leq 0.001$).

	SMC 1	SMC 2	SMC 3	SMC 4	SMC 5	SMC 6	SMC 7	SMC 8	SMC 9
SMC 1	x	0.017	0.041	0.054	0.081 **	0.088 ***	0.076 **	0.068	0.064
SMC 2	<i>0.99</i>	x	0.024	0.037 ***	0.064 ***	0.071 ***	0.059 ***	0.051	0.047
SMC 3	<i>0.61</i>	<i>0.051</i>	x	0.012	0.039 ***	0.047 ***	0.035 ***	0.027	0.023
SMC 4	<i>0.25</i>	<i><0.001</i>	<i>0.86</i>	x	0.027 **	0.034 ***	0.022	0.015	0.010
SMC 5	<i>0.004</i>	<i><0.001</i>	<i><0.001</i>	<i>0.01</i>	x	0.007	0.005	0.013	0.017
SMC 6	<i>0.001</i>	<i><0.001</i>	<i><0.001</i>	<i><0.001</i>	<i>0.97</i>	x	0.012	0.020	0.024
SMC 7	<i>0.01</i>	<i><0.001</i>	<i><0.001</i>	<i>0.17</i>	<i>0.99</i>	<i>0.82</i>	x	0.008	0.012
SMC 8	<i>0.18</i>	<i>0.055</i>	<i>0.79</i>	<i>0.99</i>	<i>0.99</i>	<i>0.96</i>	<i>0.99</i>	x	0.004
SMC 9	<i>0.77</i>	<i>0.88</i>	<i>0.99</i>	<i>0.97</i>	<i>0.99</i>	<i>0.99</i>	<i>0.99</i>	<i>0.99</i>	x

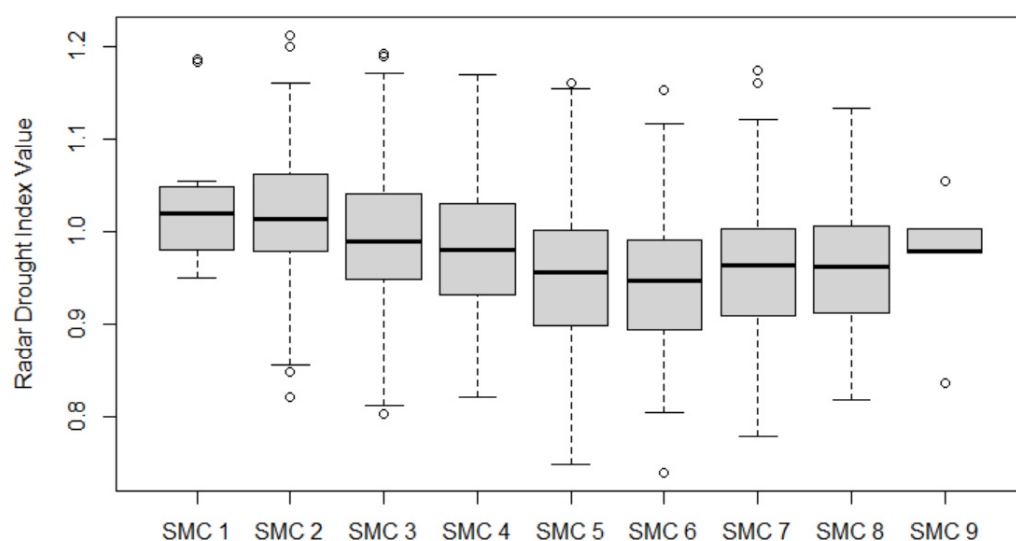


Figure 16. Boxplot diagram showing a decreasing trend of mean radar drought index values for soils with higher moisture classes.

4. Discussion

The aim of this study was to investigate the potential of S-1 data for obtaining temporally and spatially high-resolution information of drought affected forest stands. Due to the increasing risk of forest fires and increase in fire induced tree cover loss, this information is of great importance for forest management. The results of this study showed that the production of meaningful, temporally and spatially high-resolution drought detection maps from S-1 radar data is possible using the RDI calculation. The introduced method of RDI calculation represents an efficient way to reduce (signal noise) or exclude (viewing geometry) systematic influences on the signal. The plausibility of the produced spatially high-resolution drought detection map of 2020 was shown by comparisons to soil moisture classes and topographic indices (see Figures 15 and 16). The mean RDI values of temporally high-resolution drought detection maps (see Figure 12) showed a high correlation ($R^2 = 0.9678$) to moving 30-day average temperature values in 2020 (see Figure 13). Therefore, meaningful information content of RDI regarding drought-affected forest status is assumed.

The system-specific speckle noise present in unprocessed S-1 images can limit its use for applications as those shown in this study. Straight-forward preprocessing steps (temporal and spatial aggregation) permit to overcome these limitations. Both approaches for speckle noise reduction achieved the theoretically expected reduction in signal noise [57], on one hand at the expense of temporal, on the other hand at the expense of spatial resolution.

However, both approaches have advantages and disadvantages that decide on their application. Using multitemporal averaging, the spatial information content of the S-1 raw data is retained ensuring the most detailed spatial information. At the same time, the temporal resolution of the spatially high resolution RDI maps is drastically reduced which diminishes the advantage of the superior observation frequency of S-1 compared to Sentinel-2. Using spatial averaging for speckle reduction, the temporal resolution of the RDI maps is retained at the expense of spatial detail, rendering this approach preferable when an early detection of drought-affected areas on regional scale level is required. The main disadvantage of spatial averaging is its limitation to detect small areas.

The effect of both approaches for reducing speckle noise tends to saturate with an increasing number of scenes or spatial aggregation levels. Our results suggest that not more than eight scenes per composite are required for achieving a sufficient reduction in signal noise that allows RDI calculation at the original spatial resolution of S-1 (see Figure 10). The use of additional images has only marginal effects to achieve an additional reduction of speckle noise.

Depending on rainfall characteristics, i.e., frontal rains affecting extended areas in comparison to storms or isolated showers where moisture is rather distributed in spatially scattered patches, the RDI has the potential to provide a spatially differentiated assessment of canopy moisture conditions. This is not only important information for forest ecologists, but could support the identification of fire-endangered forest areas at a spatial scale which is usually not captured in fire-risk assessments driven by meteorological observation networks, a point that should be corroborated in future studies.

The RDI products were evaluated against two spatially explicit data sets, a topographic aspect raster map and a vectorized site suitability map with special emphasis on soil water availability (SMCs). Statistically significant results were found using both evaluation datasets. The assessment for summerly dry spell in 2020 shows significantly higher RDI scores for forest-covered slopes with more sun-exposed aspect (SE to SW) and elevated daily irradiation fluxes, as well as for SMCs with lower soil water holding capacities, representing dry site conditions on the long term [49]. Given the excessive drought conditions during summer 2020, these are strong indications that detected spatial patterns of drought-affected forest areas are meaningful. This is also in agreement with previous investigations in the same area [6].

The spatially high-resolution RDI maps for the different years (2018–2021) exhibit clear differences which agree with the general trends of drought severity observed during

these years. The onset of the drought took place in summer 2018. The following year also experienced a dry phase, which was shorter and less intense. The drought phase in summer 2020 was again intense, and the effect was amplified by the fact that not only the two previous summers had been extremely dry, but also the corresponding winters tended to be low in precipitation. After winter 2020/2021 had been rainy, summer 2021 was also characterized by moderate temperatures and more precipitation than in the previous years. It has to be mentioned that these years range in the long-term average concerning precipitation and temperature. Obviously, the forest ecosystem has the capacity to swing back towards the pre-drought state within this period—to which extent this is the case, the coming years might show.

The corresponding RDI maps (Figure 11) in principle depict these inter-annual variations, but it remains open whether the subtle differences between the years 2018, 2019 and 2021 correspond to canopy conditions. The study results therefore suggest that S-1 data can efficiently support the detection of severe drought conditions in forested areas. Detection thresholds for fuel moisture mapping, however, are difficult to assess precisely owing to immense efforts required to establish adequate spatial ground sampling networks over sufficiently large and diverse terrain. Nevertheless, in future studies, thresholds for fire occurrence risk could be determined by testing RDI against fire suppression registers, active fire detections or burned area perimeters for larger study areas.

Regarding the temporally high-resolution RDI maps with reduced spatial resolution, our results shed light on the trade-off between the loss of spatial detail and the resulting ability to monitor progressive drought in forests at previously unattainable short time steps (Figure 12). The mean RDI values of temporally high-resolution drought detection maps (see Figure 12) showed a high correlation ($R^2 = 0.9678$) to a moving 30-day average temperature values in 2020 (see Figure 13). Therefore, meaningful information content of RDI regarding drought-affected forest status is assumed. In contrast, the relationship between mean monthly precipitation and mean RDI values are rather weak ($R^2 = 0.5091$). A possible reason could be the appearance of very heavy precipitation events in summer 2020, with only a relatively small lasting effect for forest water supply and forest water storage. Nonetheless, the drought period in 2020, indicated by increasing monthly average temperatures and decreasing monthly average rainfall, is well detected by increasing mean RDI values. For further studies, it might be useful to test the relationship between RDI and weather records at finer (weekly) time intervals.

5. Conclusions

As a trade-off regarding necessary pre-processing steps, the spatial quality of subsequent intra-annual maps is less accurate compared to the annually produced spatially high-resolution RDI maps. Nonetheless, the spatial patterns of drought stress-affected areas are well visible using a temporally higher resolution of S-1 images at the cost of spatial resolution. Regarding the objective of application, that trade-off discussion is necessary: The post-event documentation of impacts is available at a spatially high resolution, but only on a yearly basis. On the other hand, regarding the necessity to approach the challenges of climate change in temperate forests, frequent intra-annual monitoring becomes more important and can be a key factor for operational use regarding a timely anticipation of potentially harmed areas. Although these maps are only available at a coarser resolution, they can be very supportive to arrange follow-up terrestrial observations. Due to the independence from cloud cover and daylight a high temporal density of usable data can be achieved, while a temporally dense observation based on optical data such as Landsat or Sentinel-2 is likely to be impaired by overcast at the time the sensor passes the area of interest. This makes it possible to generate drought maps for a given time, e.g., directly before a terrestrial survey.

Apparently, the preference for an RDI product is largely determined by the respective application scenario. If the best possible spatial resolution is required, there is no alternative to reducing the SAR-typical speckle component through temporal image compositing.

Since droughts are usually slow processes on a time scale of weeks, this is also the most appropriate approach to retrospectively assess the ecological impacts on forest ecosystems. However, when it comes to monitoring summer drought events as continuously as possible in view of the increasing risk of fire, the optimization of the SAR signal through spatial averaging is unrivaled.

In future studies, thresholds for risk of fire occurrence could be determined by testing RDI against fire suppression registers, active fire detections, or burned area perimeters. In addition, RDI could also be compared to canopy moisture proxies of optical systems (e.g., S-2 data), such as the moisture stress index. Future research might aim to test the relationship between RDI and weather records at finer (weekly) time intervals. Another option would be to compare RDI values with existing forest fire hazard indices from weather data for larger study areas.

Based on the produced RDI maps in this study and regarding the different objectives of forest monitoring, it seems reasonable to focus further studies on both, radar data and optical data, to provide spatially and temporally dense information for a meaningful assessment of forest vitality that can be used, among others, for mapping fire risk.

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Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. Used Sentinel-1 data can be found at (<https://scihub.copernicus.eu/>) (accessed on 15 October 2022). Sentinel-2 data has been preprocessed with the FORCE processing chain (<https://force-eo.readthedocs.io/>) (accessed on 15 October 2022). Original Sentinel-2 data can be found at (<https://scihub.copernicus.eu/>) (accessed on 15 October 2022). Used meteorological datasets can be found at (<https://cdc.dwd.de/>) (accessed on 15 October 2022) and (<https://www.wetter.rlp.de/Agrarmeteorologie>) (accessed on 15 October 2022). Used forest mask and digital elevation model can be found at (<https://land.copernicus.eu/>) (accessed on 15 October 2022). The produced high-resolution maps for Donnersberg region presented in this study are available on request from the author.

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