

Article

Impact of Vegetation and Soil Moisture on the Detection of Buried Landmines Using GPR

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Highlights

What are the main findings?

- The detectability of buried landmines in the amplitude response of an SFCW radar is significantly influenced by the properties of the vegetation layer, with the signal-to-clutter ratio having been identified as a key indicator.
- Analysis of the ground surface, vegetation reflections and the NDVI enables the environmental conditions under which reliable detection is possible to be characterised.

What are the implications of the main findings?

- In vegetation-dominated areas, it is necessary to characterise the vegetation in order to enable a reliable evaluation of the detection capability of radar systems in mine detection.
- The biomass water content correlates with detectability in the SCR and can serve as a potential parameter for estimating the point at which a phase-based analysis is required to improve detection performance.

Abstract

Vegetation above the soil surface can have a considerable influence on ground-penetrating radar (GPR) measurements, especially when shallow buried objects are to be detected. Plant water content, biomass, and the structural arrangement of leaves and stems can attenuate, scatter, or obscure reflections from both the soil surface and buried targets. This study therefore examines how different vegetation types and soil moisture conditions affect the GPR response of a shallow buried reference target under controlled laboratory conditions. For the analysis, a GPR operating in a down-looking configuration is used, which is moved across the study area on an equidistant grid. The evaluation is based on the analysis of multiple intensity pixels and heuristic statistics to characterise the radar reflections. The Normalised Difference Vegetation Index (NDVI) is used to describe the vegetation; this index approximates, in particular, the water content of the plants, as well as the relationship between biomass and dry matter content. The analysis reveals a relationship between water content, biomass volume, and the signal-to-clutter ratio (SCR) in relation to the detectability of targets. The condition of the vegetation significantly influences radar target reflection and thus the detectability of subsurface targets. In particular, higher water content in vegetation correlates with increased scattering within the vegetation layer, thereby preventing ground reflection and target reflection.

Keywords: GPR; NDVI; vegetation; surface reflection; false positive rate; statistics; detectability



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1. Introduction

The detectability of buried targets using a ground-penetrating radar (GPR) is strongly influenced by the properties of soil. These include the soil type, surface roughness, and soil moisture [1–4]. As previously demonstrated in [5], the influence of heterogeneous vegetation is also a significant factor contributing to false positives in landmine detection. This is because the increasing spread of landmines is not confined to areas alongside roads and in fields with homogeneous crops, but also occurs in areas where intensive farming is no longer practised or where land has become underused due to the presence of landmines. This raises the question of under which vegetation conditions electromagnetic waves are prevented from reaching the soil surface and penetrating into the subsurface. Research and development of GPR drone systems often rely on test sites with sandy soils [6–8]. As an alternative, predominantly homogeneous grass fields are used [7,9,10]. This sandy type of soil typically has no vegetation. Grass, on the contrary, appears as a predominantly vertical structure with a high biomass content when viewed by down-looking GPR systems. To investigate the influence of vegetative structures on the detectability of buried targets, additional plant types, mustard and periwinkle, were selected in addition to grass. Due to their structure and availability, they are well suited for investigations using our measurement system.

The results indicate a relationship between vegetation condition and the GPR response of buried targets. Visualisation using signal-to-clutter ratio (SCR) allows for a clear determination of the target's intensity and location, as well as an assessment of signal quality. As vegetation condition changes over time, long-term optical monitoring is required to identify suitable periods of GPR measurements. The standardised Normalised Difference Vegetation Index (NDVI) can therefore be used as an indicator of vegetation condition and may help explain changes in SCR.

2. Materials and Methods

Mustard and grass were grown under laboratory conditions on loamy–gravelly, water-retaining soil with controlled soil moisture. An aluminium cylinder was buried at a depth of 10 cm in the centre of each test area and served as a reference target. The aluminium cylinders have a diameter of 8 cm and a height of 5 cm.

2.1. System Setup

A VNA-based GPR system with antennas mounted on a cross table was used as the measuring system. This setup allowed the test fields under observation to be scanned with high precision using an equidistant grid, which enables the generation of A-, B-, and C-Scans without the need for image reconstruction techniques. To evaluate these scans, the test fields were sampled laterally with 3 cm spacing. The system supports a frequency range of 0.8 to 15 GHz. Due to the data structure, the measurement bandwidth can be divided into individual frequency bands of any width during post-processing. Based on the approach described in [11], a bandwidth of 4 GHz was selected. To prevent interference from direct contact with vegetation, the antenna was positioned so that its phase centre is 60 cm above the surface of the ground. With a maximum vegetation height of 30 cm, this position allows for a sufficiently large distance from the vegetation. The full specifications of the radar system are summarised in Table 1.

Figure 1 shows the antennas mounted on the cross table above the grass field. The Ultras S5 hyperspectral camera (Cubert GmbH, Germany) was mounted in the same way next to the antennas. This camera acquired 51 individual bands in the range between 450 and 850 nm.

Table 1. Radar parameterset.

Parameter	Value
bandwidth	0.8 to 15 GHz
frequencysteps	3105
bandselection	0.8 to 4.8 GHz
antenna gain (0.8 to 4.8 GHz)	4 to 10 dBi
beamwidth (3 GHz)	60°
VSWR	<3:1
antenna ground distance	60 cm
horizontal spacing $\Delta x, \Delta y$	3 cm

**Figure 1.** The antennas (blue) are mounted on the axis of the cross table above the grass test area.

To establish a reference value, the dry matter content of the plants was determined. Therefore, a reference area of biomass of a standard size was removed, weighed whilst moist and then dried. The dry matter content TS was calculated from this ratio

$$TS = \frac{m_{\text{dry biomass}}}{m_{\text{wet biomass}}}, \quad (1)$$

the gravimetric moisture content of the soils was determined in a similar way. It is calculated according to

$$w_g = \frac{m_{\text{wet}} - m_{\text{dry}}}{m_{\text{dry}}}. \quad (2)$$

To investigate the influence of vegetation, three model plants were selected that differ in terms of their structure and biomass, as can be seen in Figure 2. Grass was used as one model vegetation type. Due to its mainly vertical structure and the absence of distinct stems and woody parts, it represents a comparatively homogeneous form of vegetation. Similarly, mustard also has no woody parts. Unlike grass, mustard plants have thin, multi-layered, horizontally oriented leaves in addition to vertically oriented stems. Both plants consist predominantly of water-containing biomass. The third model plant, periwinkle, differs significantly from the plants described above. It has a diffuse structure with small, multi-layered leaves arranged on stems distributed across the entire height of the vegetation.

These stems exhibit both vertical and horizontal growth patterns. As the plant ages, the stems become partially woody, resulting in a higher volume density of the biomass. As the periwinkle is a slow-growing plant, it was, unlike the other two plants, placed on top of the soil surface. An advantage of this method was that the soil remained dry throughout the observation period. While the grass grew to around 13 cm in height, the mustard grew to over 30 cm. The layer of periwinkle that was laid down, with a focus on preserving its natural structure, measured 17 cm at the start of the observation period. The biomass and height are shown in Table 2.

Table 2. Overview of the measured volumetric wet biomass and height of the model plants.

	Height	Biomass
periwinkle	0.17 m	2.4 kg/m ²
grass	0.13 m	0.5 kg/m ²
mustard	0.30 m	0.76 kg/m ²

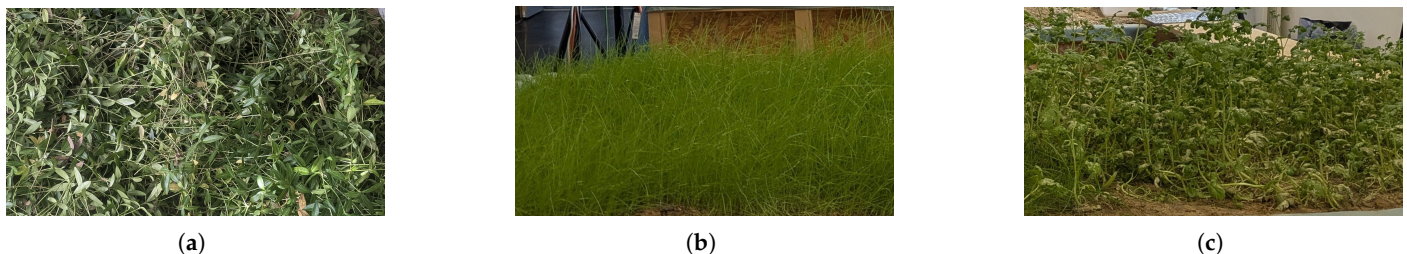


Figure 2. The three model plants of our study. The periwinkle (a) has small leaves and a diffuse structure comprising inseparable layers, as well as partially woody stems that grow horizontally. The grass (b) has a homogeneous, vertical structure. The mustard plant (c) has vertical stems and horizontal, thin, multi-layered leaves.

2.2. Methodology

A Stepped Frequency Continuous Wave (SFCW) radar determines distance information by sequentially transmitting continuous signals with discrete frequency steps within a defined frequency band. For each frequency step, the amplitude and phase of the reflected signal are recorded, thereby yielding the frequency-dependent transfer function of the observed medium. By analysing the phase variation across the frequency band, the transit time of the reflected signals can be determined. The distance profile (A-Scan) was calculated using an inverse Fourier transform on the complex frequency data. This represents the reflected-signal intensity as a function of distance.

2.2.1. Masks as Matched Filters

To determine the effect on target detection, the SCR was calculated as

$$SCR = \frac{S}{C}, \quad (3)$$

where S denotes the signal value of the target, and C denotes the clutter (background) value. This requires separating the target response from the surrounding background. For this, a classification similar to a matched filter is constructed from the voxels of the intensity matrix $I(x, y, z)$, which is determined from the range profile of the SFCW data. These masks are based on the geometric position of the buried target. As both the position (x_0, y_0) and the geometric dimensions r_t of the targets are known under the given laboratory conditions, no automatic target detection algorithm was required prior to the mask-based evaluation. In order to match the circular targets, circular masks are incorporated as filters. This principle

has already been used in [11]. The mask for the object's geometric extent can be described as the set of

$$M_t(x_j, y_k) = \begin{cases} 1, & \text{for } (x_j - x_0)^2 + (y_k - y_0)^2 \leq r_t^2 \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

for the target itself and

$$M_c(x_j, y_k) = \begin{cases} 1, & \text{for } (x_j - x_0)^2 + (y_k - y_0)^2 > r_g^2 \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

for the clutter. The radius r_g is chosen to be larger than the geometric target radius r_t . This creates a guard ring around the target, which takes the hyperbolic expansion of the radar reflection due to the longer target range into account and prevents these signal components from being included in the clutter analysis. Following multiplication by the filter and calculation of the empirical mean,

$$\mu_t(z_i) = \frac{1}{n} \sum_{(x_j, y_k) \in \Omega} M_t(x_j, y_k) \cdot I(x_j, y_k, z_i) \quad (6)$$

$$\mu_c(z_i) = \frac{1}{n} \sum_{(x_j, y_k) \in \Omega} M_c(x_j, y_k) \cdot I(x_j, y_k, z_i), \quad (7)$$

with n is calculated as

$$n = \sum_{(x_j, y_k) \in \Omega} M(x_j, y_k) \quad (8)$$

and represents the number of pixels that are set to 1 in the mask. From Equation (6), a new A-Scan is calculated depending on the depth z_i . Given the ratio of target to clutter, Equation (3) results from the initial intensity matrix $I(x, y, z)$,

$$SCR(z) = \frac{\mu_t(z)}{\mu_c(z)}. \quad (9)$$

2.2.2. Influence of Vegetation

The effective permittivity of a vegetation layer is mainly governed by the water content of the plant material, as the relative permittivity of water is significantly higher than that of dry plant matter. Changes in dry matter therefore affect the GPR signal response mainly indirectly, via changes in water content and its distribution. Thus, the vegetation layer has a significant influence on GPR signal response. In addition to their volumetric biomass proportion, vegetation layers differ primarily in their dry matter content.

As water exhibits a frequency dependence due to its relaxation time, the permittivity of the vegetation layer is also frequency-dependent. The dispersion can be determined using the Debye model [12].

$$\varepsilon_{r,w}(\omega) = \varepsilon_{r,w}(\infty) + \frac{\varepsilon_{r,w}(0) - \varepsilon_{r,w}(\infty)}{1 + j\omega\tau_r} \quad (10)$$

From the real part, the relaxation time $\tau_r = 9.84$ ps, the static permittivity of water $\varepsilon_{r,s}(0) = 80$, and for high frequencies, $\varepsilon_{r,w}(\infty) = 4.5$ result in a permittivity of $\varepsilon_{r,w}$. Due to the heterogeneous mixture of vegetation biomass and the air between vegetative structures, the complex refractive index model (CRIM) [10,13] is suitable for describing the permittivity

of vegetation ε_v . This model takes the permittivity of air (ε_0), the volumetric biomass θ_v and water content θ of the heterogeneous vegetation layer.

$$\sqrt{\varepsilon_v} = (1 - \theta - \theta_v) \sqrt{\varepsilon_0} + \theta_v \sqrt{\varepsilon_{v,dry}} + \theta \sqrt{\Re(\varepsilon_{r,w})} \quad (11)$$

One limitation of the CRIM is that, while it describes the contributions of water content and dry matter to the effective permittivity, it does not take into account the spatial or volumetric structure of the vegetation layer under investigation. The influence of this structure on the electromagnetic properties has already been demonstrated in [11]. In the study presented there, the same quantity of dry matter was measured both in its original plant structure and after being shredded. Shredding disrupted the natural arrangement of the plant components, thereby allowing the influence of the volumetric material content to be determined as the primary factor. The results illustrate that the geometric structure of the vegetation has a significant influence on the measured dielectric properties and should therefore be taken into consideration in modelling.

Macelloni et al. [14] employ an alternative approach. In this approach, the vegetation layer is described as a collection of predominantly vertical, elliptical cylinders on a rough surface. The cylinders, each with a specific permittivity, are arranged randomly within a homogeneous air medium. The description of vegetation structures remains a subject of current research. A key area of application is the estimation of biomass from Synthetic Aperture Radar (SAR) data. In satellite-based systems in particular, it is often not possible to penetrate the vegetation layer completely [15,16]. This is particularly significant for modelling the ground surface on the basis of satellite data.

Zhao et al. [17] investigate various approaches to describing vegetation and categorise these into three typical model classes. Methodical and semi-empirical models describe the spatial characteristics of vegetation structure. The semi-empirical approaches include, amongst others, the Water Cloud Model [18], which is used in numerous applications. Furthermore, Zhao et al. analyse the systematic changes in plant structure during different growth phases and their influence on backscattering properties.

2.2.3. NDVI

The NDVI is a common vegetation index used in remote sensing to assess the condition, density and spatial distribution of vegetation [19]. The index utilises the differing reflectance properties of plants in the red (RED) and near-infrared (NIR) spectral bands. Whilst chlorophyll-containing vegetation absorbs a large proportion of the incoming radiation in the red band, radiation in the near-infrared band is mostly reflected due to the structure of the leaves.

$$\text{NDVI} = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \quad (12)$$

The NDVI typically ranges from -1 to $+1$. High positive values indicate a healthy, dense vegetation cover, whilst values close to 0 indicate low or no vegetation. Negative values indicate strong absorption. In the analyses used in this study, the index falls within the positive range, as only vegetated areas were analysed. For this, the hyperspectral bands were used to eliminate space expansion in a similar way to GPR data. First, the respective vegetated area was identified and the mean value determined across this area. This helps to reduce anomalies caused by individual plants.

3. Results

At the start of the observation period, the field of mustard and grass was left to dry naturally in order to adapt to the local environment. At this point, the plants were growing healthily and were not under any stress due to lack of water. As shown in Figure 3, the

dry matter content determined using Equation A exhibits a continuous increase at the start of the observation period. As the periwinkle has been cut out and has no access to the water reserves in the soil, the dry matter content rises significantly faster. Although the mustard dries out slowly during the observation period, a significant increase in the dry matter content is visible towards the end, from day 14 onward. This is primarily because the moisture content decreases up to day 14. The grass, on the other hand, behaves in the opposite way at the start of the observation period. As the grass grows, its water requirement increases, reaching its maximum during the intensive growth phase, whilst the requirement then decreases [20]. This explains the initially higher dry matter content, which then falls on day 2. As the water requirement in grass is significantly lower than in mustard, the dry matter content rises only slowly and, due to its resistance to dry conditions and structure, does not reach the dry matter content of the mustard or the periwinkle during the observation period.

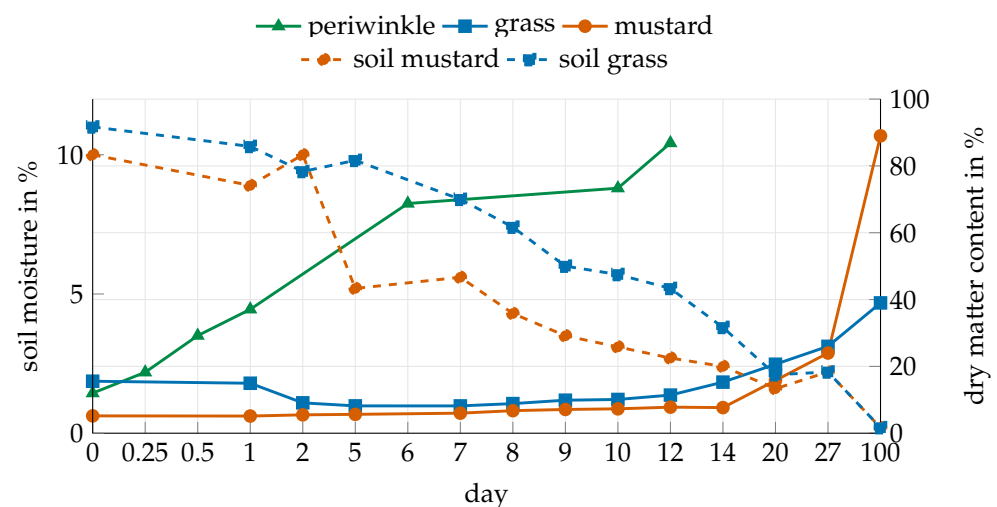


Figure 3. Changes in moisture content over the observation interval. The continuous lines (mustard, grass, periwinkle) are related to the right-hand y-axis and represent the dry matter content as a percentage. The broken lines (soil mustard, soil grass) refer to the left y-axis and represent the gravimetric moisture content of the soil as a percentage (soil moisture).

3.1. Evaluation of Masked Scans

Whenever the permittivity allows penetration of the vegetation layer, the A-Scans from $\bar{I}_{circle}$ show distinct effects over the observation period. Figure 4 shows three days from the observation period in each case.

Even at first view, the periwinkle in Figure 4a differs from the other two model plants (b,c) during the first few days of observation. The periwinkle does not allow any reflection of the soil surface. The periwinkle reflects completely. Whilst on Day 0 a reflection is present in the target depth region, on Day 3 this is ambiguous and no longer significant. This cannot be clearly explained but suggests multiple reflections within the vegetation layer or an artefact due to the evaluation procedure. A check of the C-scans generated from the distance profiles shows no target response. This becomes apparent later, as the SCR shows no target dynamics. When the periwinkle dries out, a surface reflection and a clear target reflection result.

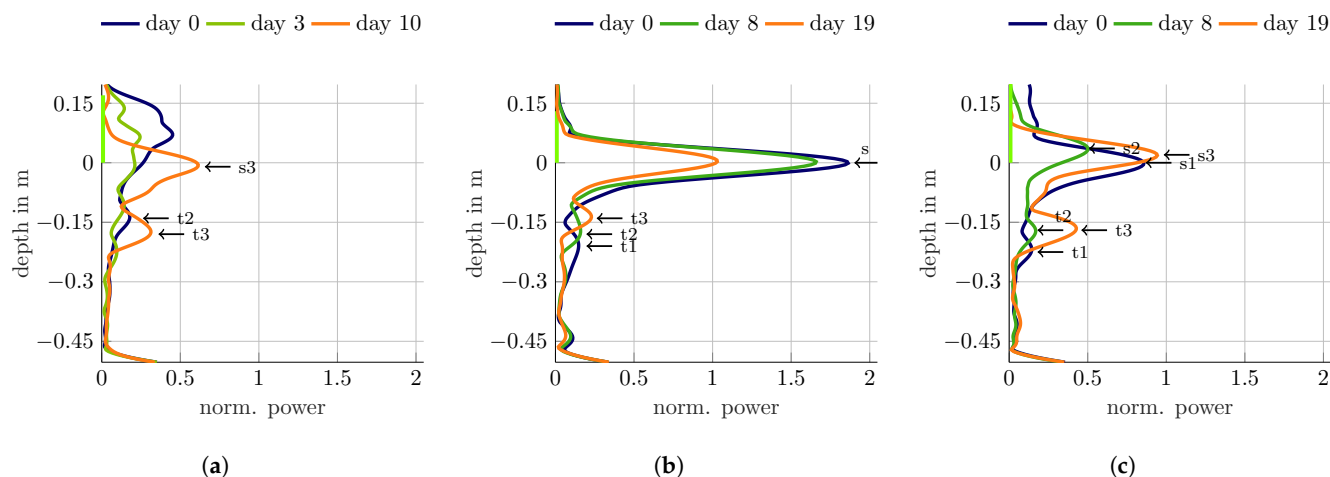


Figure 4. The graphs show various A-Scans from the observation period. On the y-axis, the vegetation area is marked in each case by a green bar. The arrows marked ‘s’ indicate the height and power of the surface, whilst ‘t’ marks the target. The green bar on the y-axis shows the height and position of the vegetation. (a) shows the evergreen, (b) the grass and (c) the mustard.

For the grass, in contrast, a clear surface reflection is visible right from the beginning. However, this decreases over the course of the observation period; this is due to the soil’s permittivity, which is reduced by the decrease in water content. The target response, marked by arrows t1 to t3, varies with soil moisture. The influence of vegetation is relatively low and is detected up to a height of approximately 13 cm above the ground surface.

The varying reflectance of the surface is exported to Figure 5. The surface reflectance of the grass decreases continuously at the same proportion as soil moisture, whereas the reflectance in the mustard is masked by the vegetation. Initially, the reflectance decreases in line with the water content. The decline is accelerated by the density of the vegetation layer. When the mustard subsequently dries out, the dry matter content increases, and the soil reflectance also rises again due to reduced scattering. As a reflection can only be measured in the periwinkle for the last two measurements, only two data points are plotted here. The increase is linked to the complete drying out of the periwinkle, as the soil moisture here remains constant.

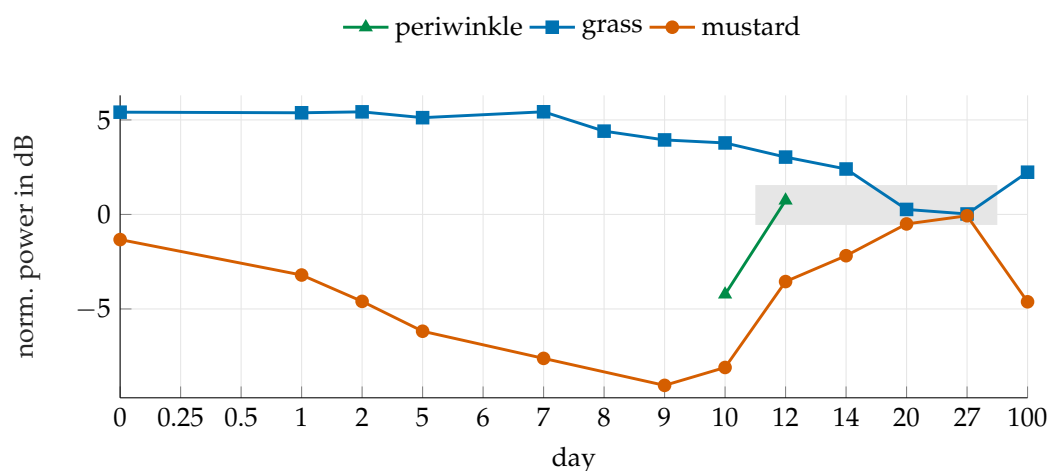


Figure 5. The three curves show the surface reflectance of the three model plants over the entire observation period. It is striking that, at the final measurement points, the reflectance values for all three plants stabilise at a similar level. At the end of the observation time, once the vegetation has dried out, all surface reflections are within the area marked by the light grey box.

In the mustard field, an overlap between the ground and the vegetation is also visible. Furthermore, it is obvious in Figure 4c that in addition to the signal strength, the height of the mustard plants is also decreasing. What is striking here is the reflection of the soil surface and the buried target. The surface reflections are more prominent on Day 0 than on Day 20, by which time the mustard has already dried out. As the signal strength at the target is similarly pronounced on these days, this can be attributed to the structural properties of mustard. Due to a lack of water, the mustard does not develop in height, thereby altering its vertical structure and leading to an increase in scatter centres. A layer of dry matter forms along the soil surface.

Figure 6 shows the A-scans recorded over the course of the days. It can be seen that in Figure 6a no surface or target reflections are initially detectable for the Periwinkle. These can be detected between Day 6 and Day 10. Whilst grass and mustard have almost identical soil moisture levels, the difference in target response performance is striking at this point. This can therefore be attributed to the vegetation layer. Also striking at this point is the ground reflection from the mustard recorded throughout the entire observation period. As can be seen in Figure 5, the power varies significantly, as does the height, which is shown in Figure 6c. One possible explanation for this would be the changing physical structure of the mustard plants, which results in constantly changing densities within the biomass and variable reflection centres.

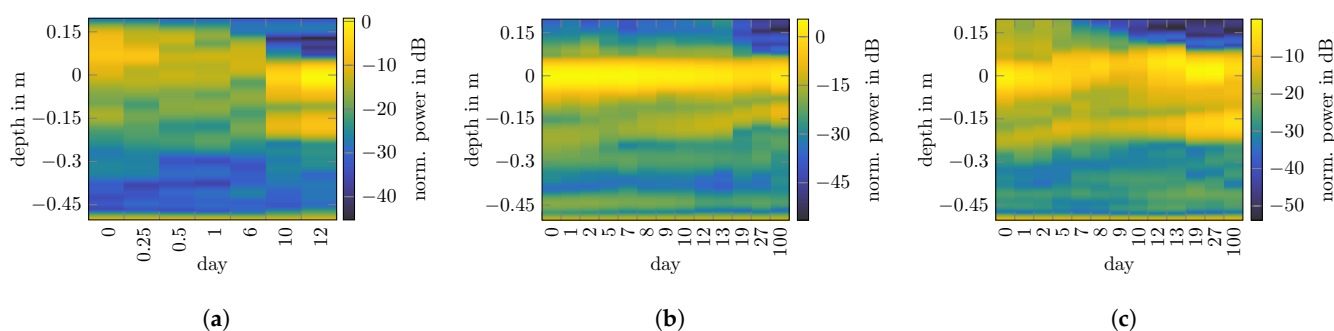


Figure 6. Time series of A-Scans during the observation period. (a) shows the periwinkle, (b) the grass, and (c) the mustard.

3.2. Signal to Clutter Ratio

The SCR has the advantage of eliminating current signal distortions that occur both in the signal itself and in the background. This allows only changes between the signal and the clutter to be efficiently represented. Figure 7 illustrates the SCR of the model plants. The signal curves for the buried target in the grass (b) and in the mustard (c) are particularly clear.

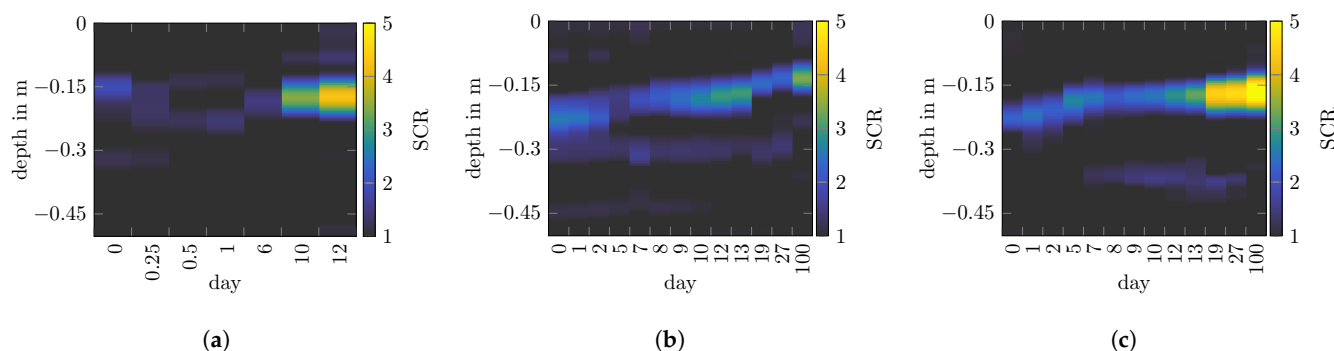


Figure 7. Time series SCR of A-Scans during the observation period. (a) shows the evergreen, (b) the grass, and (c) the mustard.

In Figure 7a it is clearly visible that as the dry mass of the periwinkle is below 50%, there is no clear reflection from the target. It is first on day 10 that the target can be clearly detected.

In Figure 7b of the SCR time series, a clear reduction in SCR is evident in the grass field on observation days 2 to 8. On the second day, the dry matter content of the grass falls by 10%, as can be seen in Figure 3. Between days 10 and 12 the content rises again, as does the SCR. Once the 20% mark is exceeded, a further dip in the SCR curve becomes apparent. On the one hand, this is due to dry matter content, and on the other hand to the soil water content, which has fallen below 1%. A similar pattern can be observed in the case of mustard. The SCR rises continuously with a marked step on day 19, which in turn correlates with the dry matter content of the mustard. This rises strongly after the soil has dried out (day 19).

3.3. Correlation Between Target Depths and Soil Moisture

The SCR profiles are particularly useful for determining the depth of the buried target. As the soil dries out, its permittivity decreases. This leads to an inverse relation between the apparent depth of the target and the soil's moisture content: as soil moisture decreases, the target appears to be at a greater depth. Figure 8 illustrates this correlation for both the grass field and the mustard field.

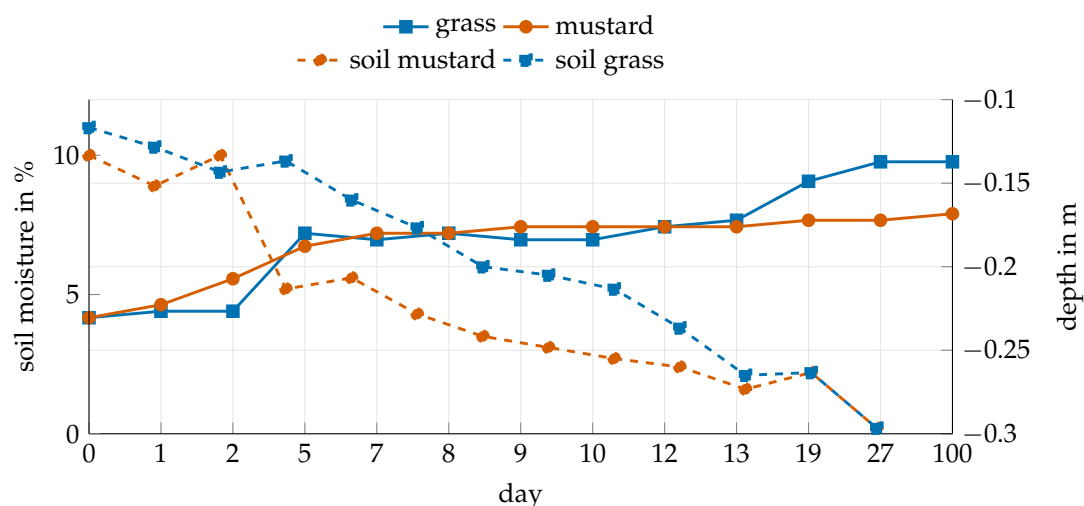


Figure 8. A representation of the correlation between soil moisture (dashed line, left y-axis) and target depth (right y-axis) during the observation period.

It can be assumed that the permittivity of the vegetation layers has a relatively minor effect on refraction. This is particularly evident in grass. Here, the dry matter content falls on the second day of observation. This means that the water content in the leaf is increasing. If the effect were similar to that of the soil, the target would have to appear deeper or at a constant depth at this point, provided the permittivity of the grass compensates for that of the soil.

No curve is given for the periwinkle, as the soil moisture here remained consistently below 1% over the observation period.

3.4. Vegetation Influence

Water scarcity triggers stress responses in vegetation. These include the closing of stomata and reduced photosynthetic activity. This leads to a decrease in the NDVI. Figure 9 illustrates the declining trend in the NDVI for all model plants. The higher NDVI values of the leaf-dominated plants (grass and mustard) are attributable to their larger photosynthetically active leaf area and higher chlorophyll content. Compared with dwarf

shrubs (periwinkle), they have a low proportion of woody biomass, which means that more near-infrared light is reflected and more red light is absorbed. This leads to higher NDVI values.

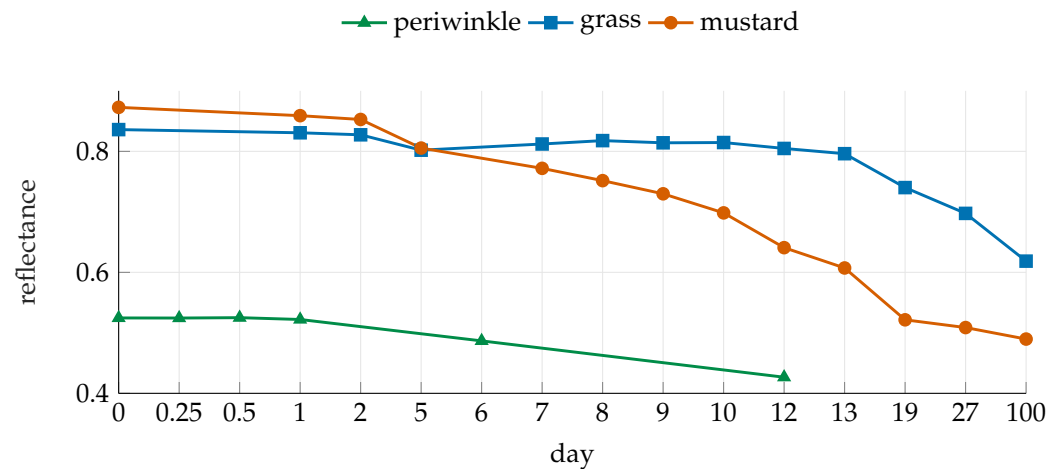


Figure 9. NDVI averaged across the vegetated area.

As the NDVI is significantly influenced by changes in water content, there is a close relation between the NDVI and the reflections measured by the GPR, as shown in Figure 10. On average, the leaf-dominated plants exhibit a similar trend to that of the NDVI. In the case of mustard, reflections are only clearly discernible up to around day 10, as the water content is subsequently too low. The grass follows its scattering intensity until around day 13; at this point both the NDVI and the GPR intensity decrease significantly. The wooden periwinkle plant also generally shows a similar trend to the measured intensity.

The periwinkle plant's high initial biomass combined with its complex structure results in a large number of diffuse scattering centres. This initially causes surface and target reflections to be superimposed. Only when the scattering intensity drops to a level similar to that of mustard and grass surfaces can target reflections clearly be identified.

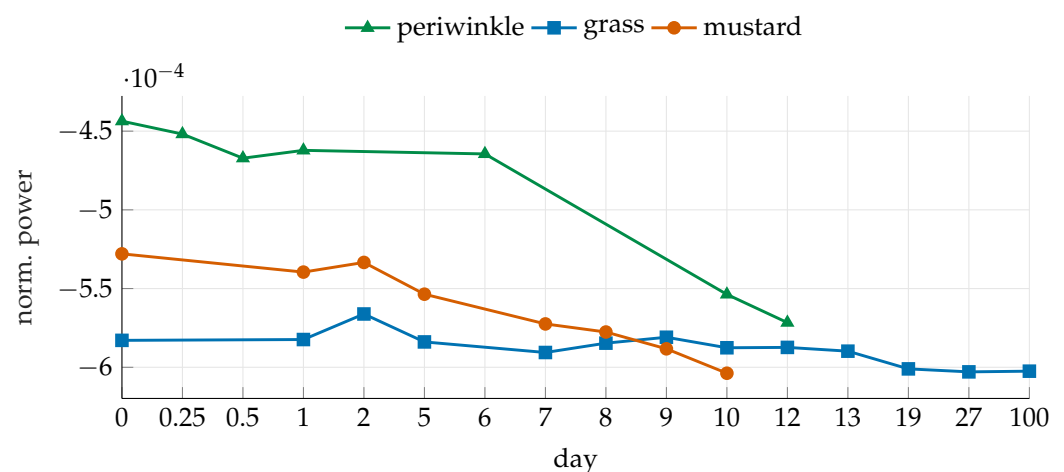


Figure 10. GPR reflection 5 cm below the maximum height of the vegetation layer.

4. Discussion

The results presented in this analysis clearly show that the vegetation layer has a significant influence on the detectability of buried objects, particularly where the area under investigation is covered by highly heterogeneous vegetation. A key influencing factor here is the reflection occurring at the soil surface. If there is no significant surface

reflection and the incident energy is instead predominantly reflected and scattered by the vegetation layer, as initially observed in the wet periwinkle scenario, this can be regarded as the cause of the failure to detect the target.

It is remarkable that below a certain moisture content of the vegetation layer, its influence apparently no longer plays a significant role. In this case, reflections occur on the same order of magnitude, which are predominantly determined by the properties of the soil. This is particularly evident in Figure 5, where reflection values of approximately -64.3 dB are observed for all model plants. To explain this observation in terms of the vegetation's water content, the biomass content from Table 1 must also be taken into account. Only by considering both water and dry matter content (TS) together it is possible to make a well-founded interpretation of the observed reflection behaviour.

$$WS = (1 - TS) \times biomass \quad (13)$$

This results in Figure 11 for the measurement days. As can be clearly seen, the initial moisture content of the periwinkle is significantly higher than that of the two leaf-dominated plants. As the CRIM does not take into account the volume effect of the total mass, it produces a significantly too low rate of change in permittivity, particularly for periwinkle and mustard. The vegetation height changes considerably over the observation period, especially for mustard and grass. As the vegetation volume becomes more compressed, the model is better able to describe the effective permittivity of the vegetative layer. In the case of upright mustard, however, it is evident that a model-based approach which explicitly represents the individual solid volumes in the airspace achieves a significantly higher degree of agreement with the observations.

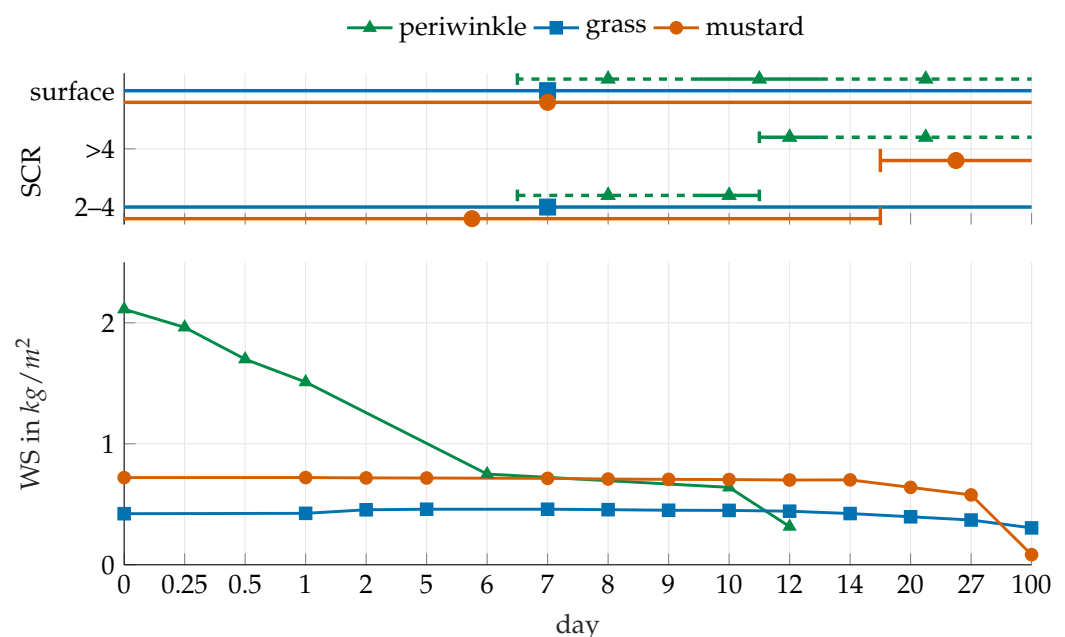


Figure 11. Biomass and water content combined for the model plants. The causal relationship between SCR and surface reflection is shown above. The dotted green line indicates the interval in which we also expect a detection, but which does not have a measurement point.

If this relation is correlated with surface reflection, a causal connection is established, showing that a sufficiently strong reflection is possible within the measurement tolerances, thus enabling reliable detection of buried objects from a threshold value of approximately 0.7. Furthermore, it can be seen that the grass vegetation remains below this threshold value throughout the entire observation period. The mustard, on the other hand,

initially hovers around the threshold value but falls below it towards the end of the observation period.

The change in structure in the model plants can be attributed to the flat, compressed dry matter. This continues to have a permittivity different from that of air. As the permittivity of plant dry matter is reported in the literature as ranging between 1.8 and 2.5, an additional transition layer is formed between the air and the soil [21]. This attenuates the permittivity discontinuity at the interface, resulting in a significantly more gradual transition. This behaviour is also reflected in the SCR.

This behaviour is also clearly reflected in the SCR analysis. Regarding target detection, it can be concluded that reliable identification of buried objects is only possible if surface reflection is a significant component of the backscattered signal. If the reflection falls below the identified threshold, scattering and attenuation effects within the vegetation layer dominate, thereby significantly reducing the detectability of the targets. The SCR does not primarily depend on soil moisture, but on the water content of the vegetation layer. The dynamics of the SCR therefore are not determined by the permittivity of the soil. The influence of soil moisture on target detection is mainly characterised by a change in the apparent target depth, which is attributable to the increased relative permittivity of the soil. There is a secondary effect on the SCR. As the water content increases, the attenuation of the radar waves increases, causing the signal amplitude of the target reflection to decrease. This leads to a reduction in the SCR, particularly at greater depths, and may result in reduced reliable detectability of deeper objects.

Figure 11 provides a plot of the model plants to demonstrate the impact of surface, SCR, and WS. It shows when the surface is reflected, as well as when the target's SCR ranges between 2 and 4 (which is clearly distinct from the noise) or rises above the threshold of 4.

Both ground surface reflectance and the characteristics of the vegetation layer can be used to assess the detectability of buried objects. In the case of ground-level vegetation, there is a strong correlation between the NDVI and radar reflectance. It is therefore useful to carry out a preliminary analysis of the study area using spectral remote sensing data.

Furthermore, the NDVI enables an estimate of the biomass present. In combination with information on the water content of the vegetation, conclusions can thus be drawn regarding the expected attenuation and scattering of electromagnetic waves. The spectral characterisation of the vegetation cover can therefore serve as a suitable tool for estimating the detectability of buried objects in advance and for identifying potentially critical areas [19,22].

In closing, however, it should be pointed out that further analysis may be required if the biomass and moisture content of the vegetation are high. The phase can be easily evaluated from the GPR depth profiles. It is largely insensitive to interference and allows detection even when there is low transmission through layers of different permittivity. Figure 12a shows the phase at the target depth below the periwinkle as early as day 0.5. Figure 12b shows the corresponding intensity distribution. This is obtained from a horizontal cross-section through the intensity matrix ($I(x,y,z)$). As can be seen, no clear signature can be identified here. This phenomenon is already shown in Figure 6a.

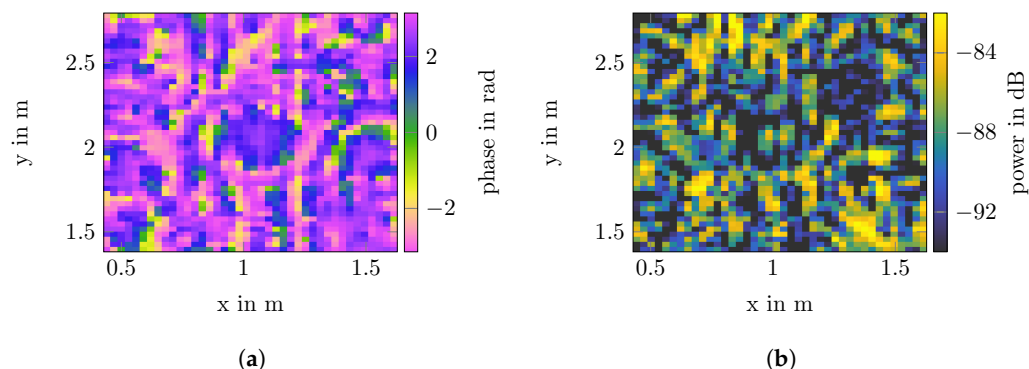


Figure 12. Phase C-Scan evaluation of the target under the periwinkle on day 0.5 in (a) and the power in the target depth that shows no target signature, (b).

5. Conclusions

The influence of vegetation layers can thus be quantified and used as a measure of the level of vegetation cover at which an analysis of phase information becomes necessary. The system should therefore be expanded to analyse both the amplitude and the phase of the radar signal. Furthermore, the measurement setup should be supplemented to include the analysis of an additional frequency range, from which conclusions can be made about the roughness and scattering properties of the vegetation. It is also possible to reduce the effects of uniform background noise through the use of unsupervised learning methods, such as Principal Component Analysis (PCA) [23].

The feature extraction carried out in this paper is also suitable for predicting the detectability of landmines under different environmental conditions. Such a prior analysis can likewise be carried out using data-driven analytical methods. The approach presented thus provides a valuable basis for the classification, detection and assessment of the detectability of landmines under varying environmental conditions.

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