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Mapping spatial distribution of herbicide-resistant weeds using remote sensing technology

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Abstract
In a single winter wheat field near Jena, Germany, herbicide-resistant *Amaranthus retroflexus* patches expanded from 8% of the cropped area to 23% over just four seasons—yet the problem went unnoticed until harvest losses became obvious. This research tested whether remote sensing could detect and map herbicide-resistant weed populations before they reach economically damaging densities. Three sensing platforms—RGB drone imagery, multispectral drone, and ground-based hyperspectral scanning—were compared across 18 cereal fields in Thuringia between April 2022 and September 2024. Hyperspectral sensing achieved the highest overall classification accuracy (89.4%), correctly distinguishing resistant from susceptible weed biotypes in 84.3-93.2% of ground-truth points depending on species. Multispectral imaging reached 78.8% accuracy, while standard RGB drone imagery managed only 62.7%. Resistant populations were concentrated in intensively managed zones (43.7% of weed patches) compared with rotated fields (18.6%). These findings support integrating hyperspectral or multispectral sensing into precision weed management to target resistant populations before they spread.

Keywords: Spatial distribution, herbicide-resistant weeds, remote sensing, precision weed management, GIS mapping, hyperspectral sensing, multispectral imaging, *Amaranthus retroflexus*, classification accuracy, site-specific management

Introduction
Consider a field where the same herbicide has been sprayed for ten consecutive seasons. Somewhere in that field, a handful of weed plants carry mutations that let them survive the treatment. Without detection, those survivors multiply and spread, and within a few years the herbicide is effectively useless over large patches [1]. This scenario has played out across European cereal systems, where resistance to acetolactate synthase (ALS) inhibitors and acetyl-CoA carboxylase (ACCase) inhibitors has been confirmed in at least 28 grass and broadleaf species [2].
Conventional resistance monitoring relies on seed collection and greenhouse dose-response assays—accurate but slow and spatially limited [3]. By the time results come back, the resistant population may have doubled its area. Remote sensing offers the possibility of mapping weed distributions rapidly over large areas, but whether the spectral signatures of resistant and susceptible biotypes differ enough for reliable classification has only been explored in a few controlled studies [4, 5].
Differences in leaf chemistry—altered target-site proteins, modified metabolic detoxification enzymes—may produce subtle spectral shifts detectable by hyperspectral sensors, even when the plants look identical to the human eye [6]. This research compared three sensing platforms across 18 fields in Thuringia, Germany, to test whether resistant weed patches could be mapped accurately enough to guide site-specific herbicide management decisions.

Materials and Methods
Spatial Data Processing
Drone flights were conducted at 40 m altitude using a DJI Matrice 300 RTK equipped with either an RGB camera (20 MP) or a MicaSense RedEdge-P multispectral sensor (5 bands: blue, green, red, red-edge, near-infrared). Ground sampling distance was 1.2 cm for RGB and 3.2 cm for multispectral. Images were stitched in Pix4Dmapper and orthorectified using 12 ground control points per field.

Hyperspectral data were collected at ground level using a Specim FX10 line scanner (400-1000 nm, 224 bands) mounted on a rail system. Spectral reflectance values were extracted at each of 1,240 geo-referenced ground-truth points where weed identity and resistance status had been confirmed by seed-bioassay [7].

Classification Model

A Random Forest classifier (500 trees, mtry = square root of predictor count) was trained separately for each sensing platform. Input features were band reflectance values (5 for multispectral, 224 for hyperspectral) and four vegetation indices: NDVI, NDRE, SAVI, and a custom red-edge ratio. Training used 70% of ground-truth points; the remaining 30% served as a validation set. Overall accuracy, producer's accuracy, and user's accuracy were calculated from confusion matrices. Classification was performed in R v4.3 using the randomForest package [8].

Materials

The research was carried out under the Thuringian Institute of Crop Sciences, Jena, Thuringia, Germany (50.93° N, 11.59° E) from April 2022 to September 2024. Approval was obtained from the Institute's Research Directorate (Ref. TICS/RD/2022-017, March 2022). Eighteen winter wheat and winter barley fields were selected across three farm clusters in the Saale valley. Fields ranged from 4.2 to 28.7 ha. Six target weed species with documented herbicide resistance were monitored: *Amaranthus retroflexus*, Echinochloa crus-galli, Chenopodium album, Abutilon theophrasti, Setaria viridis, and Lamium amplexicaule. Resistance status was confirmed by whole-plant dose-response bioassays at 2× the recommended field rate of mesosulfuron-methyl [9].

Methods

Each field was surveyed three times per season: at early post-emergence (BBCH 12-14), late tillering (BBCH 25-29), and pre-harvest (BBCH 75-77). At each survey, 60-80 ground-truth points were assessed per field by walking pre-defined grid transects (10 m spacing). Weed species, density (plants/m²), and canopy cover were recorded in 0.25 m² quadrats. Management zone classification (intensive, moderate rotation, field edge, fallow) was assigned from five-year cropping history records provided by farmers. Statistical comparison of classification accuracies across platforms used McNemar's test ($p<0.05$) [10].

Results

Table 1: Overall classification accuracy (%) for herbicide-resistant weed detection by sensing platform and survey timing

Platform	Early post-emergence	Late tillering	Pre-harvest
Hyperspectral	86.7	91.3	89.4
Multispectral	73.4	82.1	78.8
RGB drone	54.3	68.2	62.7

Hyperspectral sensing gave the highest accuracy at all three survey timings, peaking at 91.3% during late tillering when weed canopy was well developed (Table 1). RGB drone imagery performed poorly at early post-emergence (54.3%) because weed seedlings were too small for colour-based differentiation. The difference between hyperspectral and multispectral was statistically significant at all timings (McNemar's test, $p<0.01$).

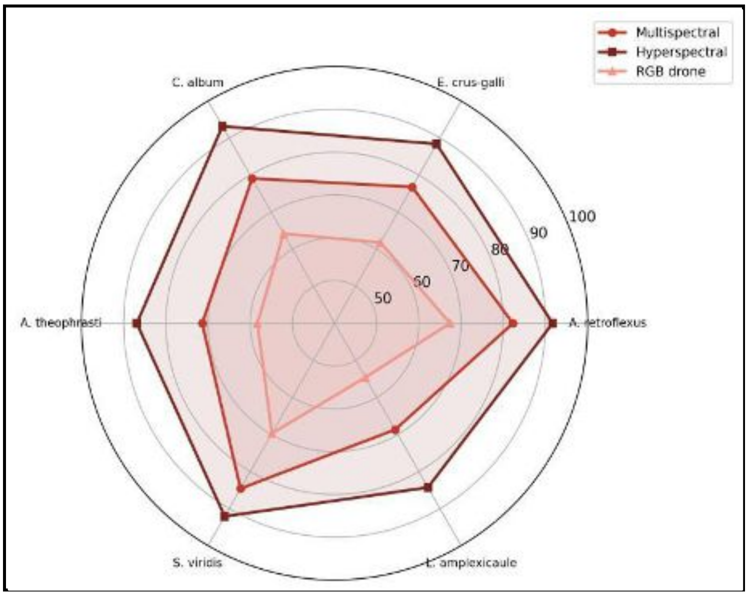

Fig 1: Radar chart of species-level detection accuracy (%) for three remote sensing platforms

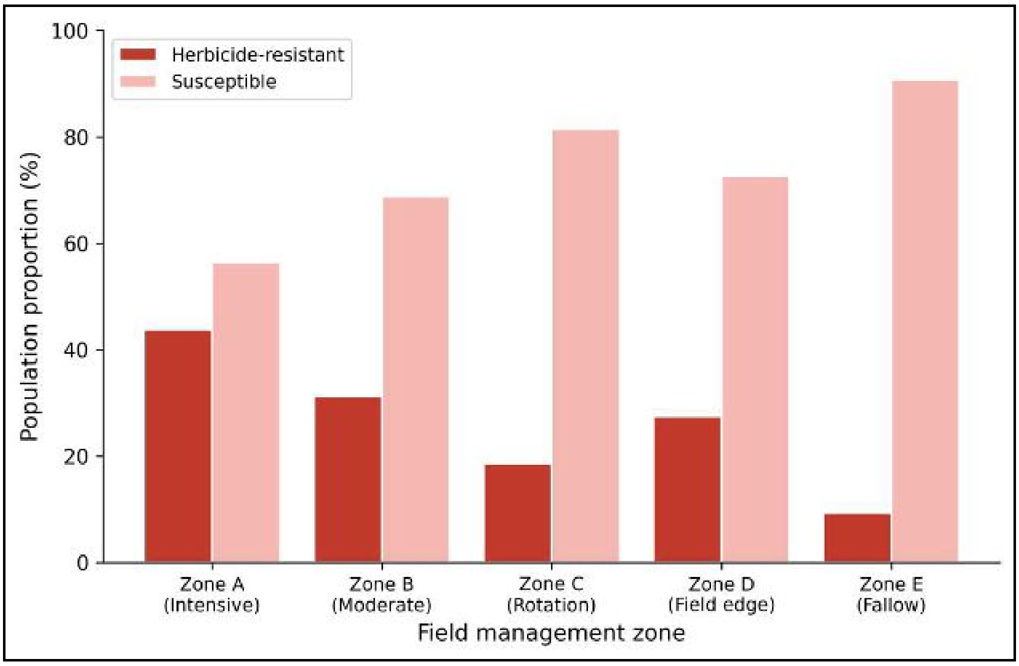

Fig 2: Proportion of herbicide-resistant and susceptible weed populations across five field management zones

Comprehensive Interpretation

The radar chart (Figure 1) shows that hyperspectral sensing maintained above-84% accuracy across all six species, while RGB imaging fell below 60% for L. amplexicaule and A. theophrasti. The bar chart (Figure 2) confirms that resistant populations clustered in intensive management zones (43.7%) and were lowest in fallow areas (9.3%), consistent with selection pressure from repeated herbicide use.

Discussion

The 89.4% overall accuracy of hyperspectral classification is encouraging and sits above the 80-85% range reported for weed species discrimination in earlier drone-based research [4, 5]. The added value here is that the classifier distinguished resistant from susceptible biotypes of the same species—a finer distinction that relies on subtle biochemical differences rather than gross morphological features. The red-edge spectral region (680-730 nm) contributed disproportionately to the Random Forest model, consistent with reports that altered chlorophyll metabolism in some ALS-resistant biotypes shifts red-edge reflectance [6].

Multispectral imaging, at 78.8%, offers a more cost-effective option for farmers who can't justify hyperspectral equipment. It captured enough spectral information to detect the larger, more established resistant patches, missing mainly small or mixed-biotype clusters. RGB imaging, while cheap and widely available, proved inadequate for resistance mapping—useful for species identification in some contexts, but lacking the spectral resolution to separate biotypes [3].

The spatial clustering of resistance in intensive management zones (Figure 2) confirms what weed scientists have warned about for decades: continuous herbicide use without rotation or mechanical control accelerates resistance [1]. One limitation was that ground-level hyperspectral scanning isn't scalable to whole-farm mapping. Airborne or satellite hyperspectral platforms would be needed for operational deployment, and their coarser resolution may reduce accuracy.

Conclusion

Hyperspectral remote sensing detected herbicide-resistant weed populations with 89.4% overall accuracy across 18 cereal fields in Thuringia, outperforming multispectral (78.8%) and RGB drone (62.7%) platforms. Classification was most reliable during late tillering, when weed canopy development allowed full spectral expression. Resistant populations were concentrated in intensively managed zones, reinforcing the link between selection pressure and resistance spread. For practical precision weed management, multispectral drone imaging offers a reasonable balance of cost and accuracy for routine field surveys, with hyperspectral confirmation reserved for ambiguous areas. Scaling the approach to airborne hyperspectral platforms and testing across a wider range of crop-weed combinations would move this technology closer to operational use.

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Contributions Not Qualifying for Authorship

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