

UAV-BASED SOIL ORGANIC CARBON ASSESSMENT IN COMPLEX TERRAIN: A REVIEW OF SENSING PATHWAYS, TERRAIN CONTROLS AND MODELLING STRATEGIES

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ABSTRACT

Soil organic carbon (SOC) is distributed unevenly across landscapes because carbon inputs, decomposition, erosion, deposition, soil moisture and management seldom vary independently of one another. Unmanned aerial vehicle (UAV) platforms have made field-scale SOC assessment technically feasible, yet variable terrain alters both the true carbon pattern and the remote-sensing signal from which it is inferred. This review develops a terrain-explicit framework for UAV-based SOC assessment by synthesising published work on UAV multispectral, hyperspectral, RGB and LiDAR sensing, satellite-assisted mapping and terrain-augmented digital soil mapping. It departs from earlier SOC remote-sensing reviews by treating terrain as an organising variable instead of one predictor among many. Studies from erosion-prone cropland, hummocky ground moraine, semi-arid farmland, sloping vegetable fields, mountainous tobacco fields, coastal wetlands, tropical forest, desertified land and permafrost gullies show that the best UAV models cannot be identified by sensor type alone. Their performance depends on sampling design, bare-soil timing, surface moisture, crop residue, canopy obstruction, topographic covariates and whether the validation scheme tests transfer beyond the calibration field. Random forest, XGBoost, support vector methods, partial least squares regression, deep neural networks and hybrid geostatistical models each perform well under particular data conditions, but none of them removes the need for pedological reasoning. We propose a workflow that links UAV observation, terrain stratification, laboratory calibration, model validation, uncertainty mapping and land-management interpretation. Terrain-aware UAV-SOC assessment is most reliable when spectral information is read together with geomorphic position, hydrological setting and soil redistribution, particularly where erosion and deposition create sharp SOC contrasts within a field.

KEYWORDS: digital soil mapping; LiDAR; machine learning; multispectral imagery; soil organic carbon; topographic position index; unmanned aerial vehicle; variable terrain

1. INTRODUCTION

Soil organic carbon makes up a small fraction of soil mass, yet its agronomic and climatic importance is large. It governs aggregate stability, water retention, nutrient cycling, biological activity, resistance to erosion and the resilience of cropping systems. Soils also hold one of the largest terrestrial carbon pools, so even modest errors in SOC stock estimates carry weight for carbon accounting and land-management policy (Angelopoulou et al., 2019; Batjes, 1996; Lal, 2004; Smith, 2004; Stockmann et al., 2013). SOC is still measured mainly in the laboratory, because dry combustion, Walkley-Black oxidation and related methods give dependable point values. Their weakness lies in spatial support. A single field may include eroded shoulders, compacted wheel tracks, depositional hollows, old management boundaries, patches of crop residue and hydrological contrasts, and a handful of samples cannot represent all of them.

Remote sensing helps to close this spatial gap by relating soil properties to spectral and terrain covariates (McBratney et al., 2003; Mulder et al., 2011). Visible, near-infrared and short-wave infrared wavelengths have a long history in soil spectroscopy, since organic matter, iron oxides, clay minerals, carbonates and moisture all influence reflectance (Angelopoulou et al., 2019; Bartmiński et al., 2024; Baumgardner et al., 1985; Ben-Dor & Banin, 1995; Stenberg et al., 2010). Satellite imagery offers wide coverage and repeated acquisitions, but field-scale SOC mapping frequently needs finer spatial detail and more flexible timing. UAVs meet this need because they can be flown when the soil is bare, when crop vigour reflects underlying soil constraints, or when illumination and moisture conditions are acceptable. They carry RGB, multispectral, hyperspectral, thermal and LiDAR sensors and can deliver centimetre-scale imagery that reveals within-field variation lost in coarser satellite pixels (Biney et al., 2023; Colomina & Molina, 2014; Guo et al., 2020; Heil et al., 2022; Zhang & Kovacs, 2012).

The advantage of UAVs is clearest in variable terrain. Terrain shapes SOC through erosion, deposition, drainage, solar radiation, vegetation productivity and the ease with which land can be managed (Doetterl et al., 2016; Moore et al., 1993; Van Oost et al., 2007). Convex shoulders tend to lose fine particles and organic matter under tillage or water erosion, whereas concave footslopes and depressions may accumulate the transported material. On humid or poorly drained sites, wetness can preserve SOC, restrict root growth or change the spectral response through moisture. In forests and wetlands, terrain affects canopy height, biomass, inundation and sedimentation, so UAV optical sensors rarely see bare soil at all. Work on hummocky ground moraine, erosion-prone Czech cropland, sloping vegetable fields in Japan, Tibetan thermo-erosion gullies, mountainous tobacco fields, tropical rainforest and coastal *Spartina alterniflora* wetlands shows that terrain governs both the SOC process and the path by which the sensor records it (Chen et al., 2025; Ding et al., 2023; He et al., 2025; Qi et al., 2025; Takata et al., 2023; Wehrhan & Sommer, 2021).

UAV-based SOC assessment therefore has to solve two problems at once. The first is prediction: how well can measured SOC be estimated from spectral, terrain, structural and management covariates? The second is interpretation: does the mapped pattern represent organic carbon itself, a correlated soil property, a vegetation response to fertility, transported sediment, surface moisture, or some interaction among these? Many studies report strong performance with random forest, XGBoost, support vector regression, artificial neural networks or partial least squares regression. These results are useful, but their meaning shifts when validation is local, when samples are few, or when calibration and prediction areas differ in slope, crop stage or surface condition (Biney et al., 2023; El Jamaoui et al., 2024; Tripathi et al., 2024).

This review examines the UAV-SOC literature from that interpretive standpoint. We do not attempt to rank one sensor or algorithm as universally superior. Instead, we show how terrain should guide sampling, flight timing, covariate selection, model training, uncertainty reporting and management use, and we treat UAV assessment as a combined pedological and remote-sensing task. A high-resolution orthomosaic is only a starting point; its scientific value appears once the map is tied to soil redistribution, hydrological position, spectral physics and a defensible validation design.

2. Terrain-aware review framework and article structure

The review follows a terrain-mediated chain of observation. Carbon is produced and redistributed within a landform, UAV sensors record an optical or structural expression of that landform, models convert covariates into SOC estimates, and the resulting map is used for management. Earlier reviews have usually arranged SOC remote-sensing evidence by platform, wavelength range or regression algorithm (Angelopoulou et al., 2019; Mulder et al., 2011). Such an arrangement works well for cataloguing methods, but it can obscure why a model succeeds in one field and fails in the next. A UAV flight over a flat bare field records a different mixture of soil colour, moisture, organic matter, residue, vegetation vigour, shadow, surface roughness and terrain geometry from a flight over a permafrost gully, a wet footslope or a forest canopy. Because variable terrain controls both SOC formation and the reliability of the signal, a terrain-first structure suits this review better. Figure 1 summarises the sequence as a linear workflow.

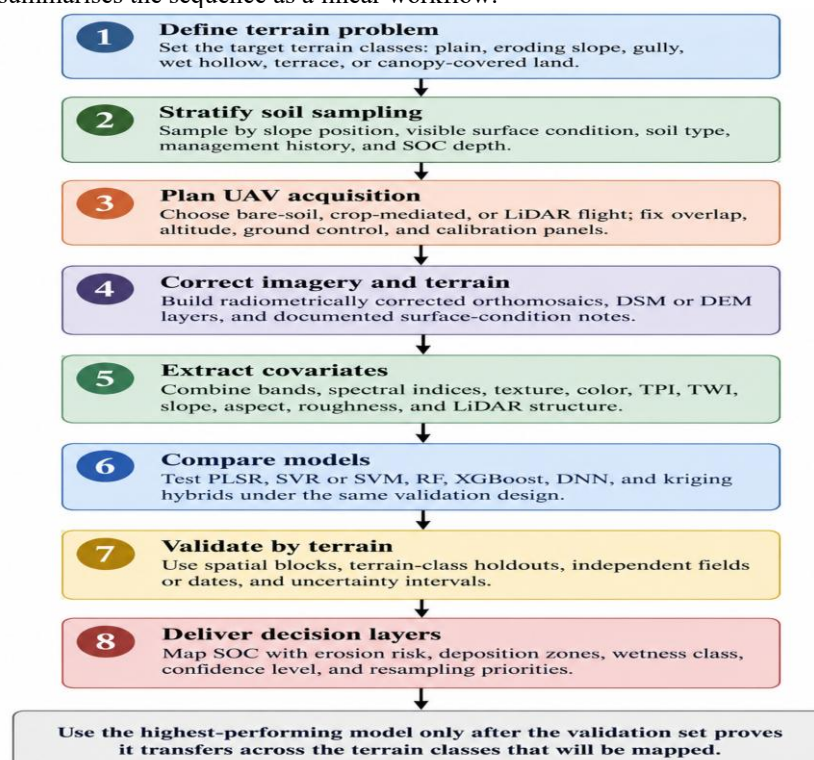


Figure 1. Linear terrain-aware workflow for UAV-based SOC assessment.

The sections move from concept to operational use. We first set out the need for high-resolution SOC assessment and describe the evidence base, then separate direct and indirect UAV signal pathways and discuss the terrain processes behind them. These processes are then translated into acquisition and preprocessing choices, model families are compared, and the review closes with transferability, uncertainty, applications and research priorities.

The framework in Figure 1 is the central contribution of the review. Terrain enters it at the sampling stage, during flight planning, in the choice of covariates, in the interpretation of feature importance and in the final map, rather than being appended near the end of modelling as a convenient raster layer. The distinction matters because a model can post a high validation statistic while learning a site-specific mixture of soil colour, residue, wetness and slope position. In variable terrain, a useful SOC map has to show where the prediction rests on soil processes and where it is only a statistical approximation. This emphasis separates the present review from general SOC spectroscopy reviews and from UAV precision-agriculture papers that concentrate on image resolution or algorithm performance. Figure 2 illustrates the setting the framework is designed for, in which a single field contains eroding slopes, a gully and depositional ground.



Figure 2. Conceptual view of UAV-based SOC assessment over eroding and depositional terrain.

3. Evidence base and review logic

The literature examined comprised journal articles, reports and book chapters on SOC mapping, UAV remote sensing, soil spectroscopy and digital soil mapping. Duplicate records were removed by matching titles and digital object identifiers. Priority was given to peer-reviewed studies that directly examined SOC, soil organic matter (SOM) or SOC stocks using UAV imagery, UAV LiDAR, terrain covariates or closely related remote-sensing approaches. Broader reviews and soil spectroscopy studies were used to support background statements on VNIR-SWIR spectral behaviour, digital soil mapping and soil-terrain relationships. Documents that did not deal with soil were excluded.

Most of the core evidence is recent. Guo et al. (2020) used time series of UAS multispectral images to map field-scale SOC under winter oilseed rape and showed that crop growth signals can partly compensate for vegetation cover when bare soil cannot be imaged. Wehrhan and Sommer (2021) combined UAS multispectral imagery with the topographic position index (TPI) in a hummocky soil landscape and placed their samples along an erosion-deposition gradient. Heil et al. (2022) mapped fine-scale SOM from UAV-derived soil colour in German loess cropland and tested transfer to a neighbouring field. Lian et al. (2022) used low-altitude aerial images and fractional vegetation cover to improve SOC stock prediction in a fragmented desertified landscape. Ding et al. (2023) applied UAV covariates together with soil and terrain attributes to thermo-erosion gullies on the Tibetan Plateau, and Biney et al. (2023) tested bare-soil UAV bands, spectral indices and terrain attributes in an erosion-prone agricultural field. Takata et al. (2023) used drone-derived elevation models, topographic indices and soil colour to map surface organic carbon in eroding, sloping vegetable fields on Andosols. These studies form the backbone of the review.

More recent papers carry the terrain problem beyond bare cropland. Cutting et al. (2024) showed that topographic features derived from a LiDAR survey improved intra-field SOC quantification when combined with Sentinel-2 spectral data. Using Sentinel-2A imagery, Zou et al. (2024) found that the benefit of topographic factors differed among plain, mountain and hilly regions and was greatest where topography was most complex. El Jamaoui et al. (2024) and El-Jamaoui et al. (2025) tested UAV multispectral data and machine-learning models in semi-arid agricultural soils. Tripathi et al. (2024) compared UAS and Sentinel-2A datasets in India and obtained better SOC prediction from the UAS data. Qi et al. (2025) used UAV multispectral imagery and red-edge-modified indices in mountainous tobacco fields, He et al. (2025) combined UAV multispectral and LiDAR data in *Spartina alterniflora* wetlands, and Chen et al. (2025) used UAV hyperspectral and LiDAR data in tropical rainforest. Song and Zhang (2026) examined UAV hyperspectral imagery across heterogeneous farmland in the Huangshui River Basin.

Foundational studies define the wider methodological space. Angelopoulou et al. (2019) reviewed remote-sensing techniques for SOC estimation and identified persistent difficulties with atmospheric, radiometric and geometric correction, vegetation cover, soil moisture and roughness. Mulder et al. (2011) reviewed remote sensing in soil and terrain mapping and placed SOC prediction within the longer tradition of digital soil mapping. Viscarra Rossel et al. (2016) demonstrated the value of spectral libraries for characterising soil at broad scales. Matinfar et al. (2021) showed that combining geomorphometric and remote-sensing covariates can outperform remote sensing alone and that hybrid methods such as random forest with ordinary kriging can improve field-scale SOC mapping. Bartmiński et al. (2024) underlined the need to account for carbonates and spectral preprocessing when organic carbon signals are mixed with mineral signals.

Three principles emerge from this evidence. First, UAV-SOC assessment is strongest when the calibration design samples process gradients and not merely geographic space. Second, terrain variables are not interchangeable: TPI, the topographic wetness index (TWI), slope, aspect, roughness, relief amplitude, elevation and LiDAR canopy metrics each represent different mechanisms. Third, external validation is essential whenever a map is meant to be used beyond the sampled field, crop stage or landform. These principles are used to compare studies without forcing them into a single performance ranking (Tables 1 and 2).

Table 1. Terrain classes and expected implications for UAV-based SOC assessment.

Terrain class	Dominant process	SOC	Main UAV signal	Primary risks	Design implication
Flat or low-relief cropland	Management and crop growth often dominate spatial variation.	Vegetation time series, bare-soil colour, spectral indices.	Weak terrain gradients; management effects can be mistaken for SOC.	Use crop history, repeated flights and management-zone sampling.	
Convex shoulders and eroding slopes	Loss of fine particles and organic-rich aggregates.	Bare-soil brightness, red-edge indices, TPI, slope.	Exposed subsoil, residue and roughness can bias reflectance.	Oversample erosion positions and include terrain covariates.	
Footslopes and depositional hollows	Accumulation of transported SOC and fine sediment.	Terrain indices, moisture-sensitive signals, soil colour.	Wetness can mimic high SOC or obscure soil colour.	Record moisture and validate with independent footslope samples.	
Gullies and thermo-erosion terrain	Slumping, thaw, exposed layers and hydrological disturbance.	DSM, TPI, roughness, multispectral indices, field parameters.	Sharp microtopography and mixed soil horizons.	Use landform-class sampling and terrain-class validation.	
Wetlands and riparian vegetation	Sedimentation, inundation, high biomass, variable decomposition.	Multispectral vegetation indices, LiDAR elevation and canopy metrics.	Soil is rarely visible; plant species and water dominate the signal.	Model by vegetation or geomorphic class and report transfer limits.	
Forest and dense canopy	SOC linked to biomass, litter, elevation, moisture and canopy structure.	Hyperspectral vegetation indices plus LiDAR CHM and DEM.	Optical sensors cannot observe the soil directly.	Treat maps as indirect SOC estimates and validate by terrain strata.	

Table 2. Core studies informing the terrain-explicit review framework.

Study	Terrain or system	Data and samples	Best reported result	Contribution to this review
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Study	Terrain system or	Data and samples	Best reported result	Contribution to this review
Guo et al. (2020)	Winter oilseed rape field in low-relief farmland.	Six monthly UAS multispectral images; bands and three vegetation indices.	BPNN RPIQ = 2.546; ELM RPIQ = 2.380.	Crop time series can reveal SOC where terrain covariates are weak.
Wehrhan and Sommer (2021)	Hummocky ground moraine with an erosion-deposition gradient.	UAS VIS-NIR imagery, TPI; 19 pedologically selected samples in two fields.	Local MLR with 570 nm reflectance plus TPI: LOOCV R^2 = 0.91, RMSE = 0.11%.	Shows the value of targeted terrain sampling.
Heil et al. (2022)	German loess cropland.	UAV soil colour; 91 calibration and 8 external samples.	RF RMSE = 0.13% SOM; external RMSE = 0.12%.	Bare-soil colour supports fine-scale SOM mapping and transfer to an adjacent field.
Lian et al. (2022)	Fragmented desertified land, Horqin Sandy Land.	Low-altitude aerial images and fractional vegetation cover (FVC).	FVC strongly related to SOC stocks (R^2_c = 0.94).	Links UAV mapping to SOC stocks in patchy degraded terrain.
Ding et al. (2023)	Thermo-erosion gullies, Tibetan Plateau.	146 training and 20 independent samples; UAV and soil covariates.	SVM R^2 = 0.53 (training) and 0.51 (independent test).	Moderate but process-relevant prediction in disturbed terrain.
Biney et al. (2023)	Erosion-prone agricultural field, Czech Republic.	133 samples; bare-soil UAV bands, spectral indices, terrain attributes.	Merged dataset best; EGB and MARS R^2_{val} = 0.86.	Supports merged spectral-terrain models for eroded fields.
Tripathi et al. (2024)	Experimental farm, ICAR-NRRI, Odisha, India.	MicaSense RedEdge UAS and Sentinel-2A; RF and SVM.	UAS RF RPIQ = 2.57 (R^2_{cv} = 0.25); Sentinel-2A lower.	UAS data outperformed coarser satellite data, though absolute accuracy was modest.
Cutting et al. (2024)	Intra-field SOC, South-East England.	55 samples; airborne LiDAR; single and multivariate Sentinel-2.	Multivariate plus topography: validation RMSE = 0.23% (SVR) and 0.29% (RF).	Shows TWI as a context-dependent predictor.
Chen et al. (2025)	Tropical rainforest, Hainan.	UAV hyperspectral and LiDAR; 40 VIs and 101 LiDAR variables.	VI plus LiDAR DNN R^2 = 0.76.	LiDAR supports SOC estimation where the canopy blocks soil spectra.
Song and Zhang (2026)	Heterogeneous farmland, Huangshui River Basin.	296 samples; laboratory spectra resampled to UAV bands; seven transformations.	RF R^2 = 0.90; RPD = 3.11.	Hyperspectral preprocessing and multi-site sampling strengthen SOC maps.

4. UAV-observable signals for soil organic carbon

Bare-soil reflectance is the most direct UAV-SOC pathway. Organic matter generally darkens soil and lowers reflectance across the visible range, while its interaction with minerals, moisture, texture and carbonates shapes the VNIR response (Bartholomeus et al., 2008; Baumgardner et al., 1985). Bare-soil UAV studies exploit this pathway by flying after harvest, before canopy closure or after tillage, when vegetation interference is low. Biney et al. (2023) found that bare-soil UAV bands and spectral indices correlated more strongly with SOC than terrain attributes alone in an erosion-prone field, although the best results came from merging UAV bands, spectral indices and terrain data. Heil et al. (2022) showed that UAV-derived colour information can predict SOM at 1 m support when bare soil is visible, while local calibration remained

important. Song and Zhang (2026) extended this logic to hyperspectral data: they calibrated models on laboratory spectra resampled to UAV band characteristics, tested several spectral transformations and applied the best RF model to UAV images from three farmland areas.

Bare-soil reflectance is informative but fragile. Moist soil looks darker and can be mistaken for soil rich in SOC. Residue may brighten the surface or add spectral features unrelated to soil carbon. Roughness changes shadowing and bidirectional reflectance. Iron oxides and carbonates can mask or exaggerate colour-based SOC signals (Bartmiński et al., 2024; Peng et al., 2013). Bartmiński et al. (2024) showed that carbonate-rich soils need careful preprocessing and, in some cases, additional information on inorganic carbon. Wehrhan and Sommer (2021) noted that surface status, including plant cover, residue, moisture and roughness, can obscure the relationship between spectral data and SOC. A bare-soil UAV model is therefore an observation made under a narrow set of surface conditions, and it should be reported as such.

A second pathway works through vegetation. Guo et al. (2020) used monthly UAS multispectral images of winter oilseed rape and showed that crop growth can reveal underlying variation in soil fertility and SOC. The approach is helpful when bare-soil imagery is unavailable, but the target changes from direct soil reflectance to plant response. Vegetation indices may capture SOC effects through nutrient supply, water availability, soil structure and rooting conditions, yet they also respond to cultivar, disease, management, compaction and weather. The interpretation holds best where crop growth is known to be limited by soil properties and where models are trained across the relevant management zones.

A third pathway relies on structure rather than surface colour. LiDAR yields digital elevation models, canopy height models, microtopographic roughness and vegetation structure. None of these measures SOC directly, but they represent controls on organic matter input, erosion, drainage and canopy obstruction. Chen et al. (2025) found that LiDAR-derived features alone performed slightly better than optical vegetation indices for forest SOC estimation ($R^2 = 0.61$ versus 0.59) and that combining UAV hyperspectral indices with LiDAR features raised accuracy further. In *Spartina alterniflora* wetlands, He et al. (2025) reported that topographic variables accounted for roughly a quarter to a third of model importance in SOC prediction. In vegetated terrain, then, UAV-SOC assessment depends as much on ecological proxies as on direct soil spectral features.

The fourth pathway is terrain-augmented remote sensing, in which terrain variables serve as process covariates, error-correction variables or sampling strata. In the Czech erosion-prone field studied by Biney et al. (2023), high-resolution UAV terrain attributes were compared with coarser ones and combined with UAV spectral data. Wehrhan and Sommer (2021) used TPI to represent erosion-deposition position in hummocky cropland. Cutting et al. (2024) found that adding topographic data improved SOC prediction relative to single-date spectral data alone. Zou et al. (2024) showed that the value of topographic variables differs between terrain regions: no characteristic topographic factor was identified for the plain, whereas the mountain and hilly regions benefited from elevation, relief amplitude and slope. These studies support the use of terrain as a working component of the model and not as a background map layer.

5. Terrain processes that control UAV SOC prediction

Erosion-deposition gradients are the clearest terrain mechanism in cropland. SOC is preferentially lost from convex eroding shoulders, where fine particles and organic-rich aggregates are detached and moved downslope (Berhe et al., 2007; Van Oost et al., 2007). Depositional footslopes and hollows may gain SOC-rich material, although burial, moisture and altered decomposition rates can complicate the relationship (Doetterl et al., 2016). UAV imagery can resolve these gradients because centimetre-scale images capture small slope positions and management marks that disappear within satellite pixels. Wehrhan and Sommer (2021) deliberately placed samples along an erosion-deposition gradient, Biney et al. (2023) obtained better SOC maps in an erosion-prone field when UAV and terrain covariates were merged, and Takata et al. (2023) linked erosion and redeposition on sloping Andosol fields to drone-derived topographic indices. Together these findings justify terrain-stratified sampling as a core design rule.

Variable terrain also changes illumination and surface geometry. Slopes facing the sun differ from shaded slopes even when their SOC is identical. Microrelief, clods, rills and gully walls alter the shadow fraction and the apparent brightness of the soil. Orthomosaic processing can reduce geometric distortion, but it cannot remove every bidirectional reflectance and shadow effect. Figure 3 shows how the same spectral response can mean different things at different slope positions. Terrain-derived variables such as slope, aspect, roughness and TPI help a model judge whether a spectral difference is more likely to reflect soil carbon, moisture or viewing geometry. Ding et al. (2023) included TPI and roughness in their study of a Tibetan thermo-erosion gully, and Qi et al. (2025) attributed part of the difference among mountainous tobacco fields to their elevation, location and rapidly changing weather.

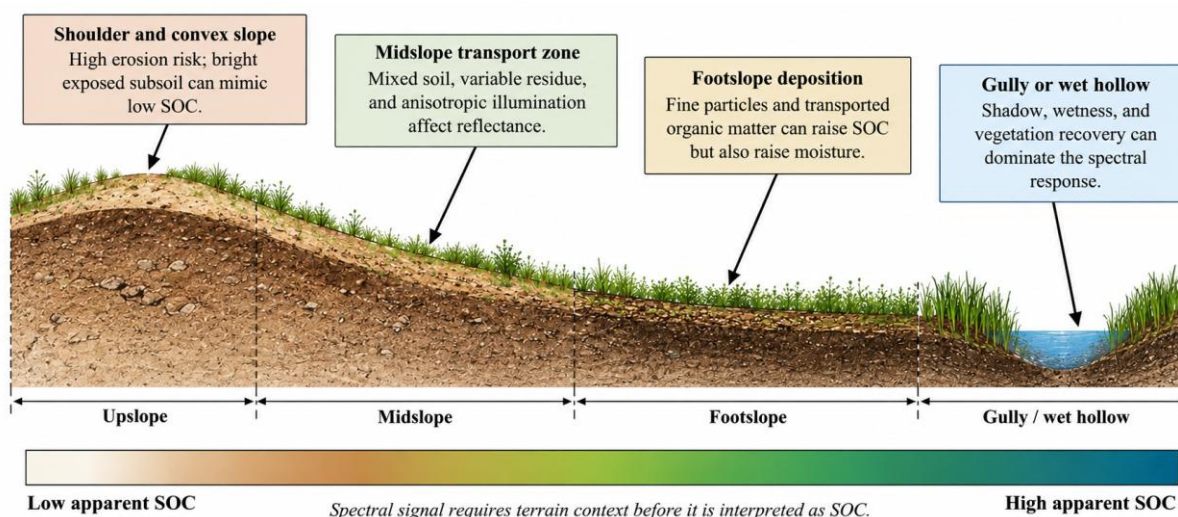


Figure 3. Terrain position modifies the interpretation of UAV spectral signals.

Hydrology links terrain to both SOC formation and spectral response. TWI, drainage position, concavity and flow accumulation indicate where water tends to persist (Moore et al., 1991; Tarboton, 1997). Moisture can raise biomass and organic inputs, slow decomposition in saturated soils, or darken bare soil regardless of its carbon content. Cutting et al. (2024) found that TWI had the highest permutation importance in their intra-field SOC models, yet it was negatively related to SOC, in contrast with results from drier climates; they attributed this to excess rainfall and poorly drained soils. The finding matters because it shows that a terrain covariate has no fixed sign. Its meaning depends on climate, drainage, soil texture and management.

Complex terrain in permafrost, wetlands and forests widens the gap between visible surface signals and the SOC pool. In thermo-erosion gullies, slumping and exposed subsurface material can change soil temperature, water content, texture and organic carbon over short distances. Ding et al. (2023) combined soil properties, field parameters, topographic variables and UAV covariates to predict SOC in Tibetan Plateau gullies and reported moderate explanatory power with strong dependence on landscape process. In *Spartina alterniflora* wetlands, He et al. (2025) used UAV multispectral and LiDAR variables and found that the contribution of topographic variables to SOC prediction was larger on mudflats (36.9%) than under non-lodging and lodging *S. alterniflora* (24.3% and 26.9%). In tropical rainforest, Chen et al. (2025) showed that canopy height and elevation variables can support SOC estimation where optical sensors cannot view the soil.

Desertified landscapes add a further terrain problem, fragmentation. Lian et al. (2022) used low-altitude aerial images and fractional vegetation cover to improve SOC stock prediction in the agropastoral ecotone of northern China. The study is relevant because patchiness is a terrain and land-degradation signal rather than a mere spectral nuisance. In fragmented systems, UAV imagery can distinguish vegetation cover, bare sand, crusted surfaces and small patches whose average condition is poorly captured by coarse maps. The SOC map becomes useful once the model connects these patches with degradation status and the recovery of carbon stocks.

Flat terrain deserves attention as well, because it may lack strong geomorphometric gradients. Guo et al. (2020) noted that common soil-forming factors can be insensitive to SOC variation in low-relief farmland. Their time-series approach dealt with this by using crop development as a spatially rich proxy for soil fertility. Terrain still matters in plains, but the relevant signal may be subtle, mediated by management, or replaced by crop response. A terrain-aware framework must therefore allow covariate priorities to differ among plains, hillslopes, gullies, wetlands, forests and fragmented drylands.

6. UAV data acquisition and preprocessing in variable terrain

Timing is the most important flight decision. Bare-soil SOC prediction needs a narrow acquisition window in which vegetation is absent, residue is limited, the surface is not saturated and illumination is stable. UAVs suit this requirement because flights can be scheduled shortly after tillage or harvest, or after a spell without rain. Biney et al. (2023), Heil et al. (2022), Qi et al. (2025) and Song and Zhang (2026) all depended on matching imagery to field sampling and surface conditions. In variable terrain, timing should also take account of slope drying, shadow and runoff redistribution, since a south-facing shoulder and a shaded hollow can be at quite different moisture levels on the same day.

Radiometric calibration cannot be skipped. Multispectral and hyperspectral cameras need reflectance panels, stable exposure, irradiance correction where available and careful handling of changing sky conditions (Aasen et al., 2015; Honkavaara et al., 2013). Without radiometric consistency, a model may learn the weather on the day of the flight instead of the SOC gradient. The risk is greater in hilly terrain, where illumination varies with aspect and local slope. Spectral preprocessing can reduce noise, but it cannot recover field conditions that were poorly controlled. Song and Zhang (2026) compared spectral transformations and obtained the strongest

results from multiplicative scatter correction combined with a first-order derivative, and Bartmiński et al. (2024) showed that derivative treatments and feature selection can be decisive in carbonate soils. Geometric quality affects every terrain-aware SOC map. Ground control points, adequate image overlap, accurate camera calibration and careful structure-from-motion processing are needed to align spectral layers, surface models, field samples and management zones (James & Robson, 2012; Turner et al., 2012; Westoby et al., 2012). A small horizontal error can shift a sample from shoulder to backslope, or from a gully wall to the depositional floor. This is especially damaging when sample plots are small or when imagery is used at centimetre resolution. LiDAR can improve structural and topographic information, but LiDAR and optical layers must be co-registered carefully before variables are extracted for modelling (Chen et al., 2025; He et al., 2025).

Surface condition should be recorded as a scientific variable. Soil moisture, roughness, residue, crusting, straw, stones, recent tillage and crop remnants can all influence reflectance, and several studies have identified them as obstacles to generalisation and not as minor noise (Angelopoulou et al., 2019; Heil et al., 2022; Wehrhan & Sommer, 2021). A terrain-aware field protocol should therefore log weather history, rainfall timing, residue cover, tillage state and visible moisture differences by slope position. In many cases a simple field sheet does more for model interpretation than one more spectral index.

Sample design must follow terrain processes. Grid sampling is simple and defensible, but it can under-represent rare landform elements such as gullies, shoulders, wet hollows and depositional fans. Stratifying samples by terrain class, soil type, management zone and visible surface condition gives the model a better chance of learning the full feature space. Wehrhan and Sommer (2021) drew on pedological knowledge to select a small number of samples along an erosion-deposition gradient. Ding et al. (2023) kept training and independent test samples in separate thermo-erosion gullies, and Song and Zhang (2026) collected 296 samples across three farmland areas. Sample placement is, in effect, part of the model architecture. Figure 4 turns this principle into a landform-based sampling and holdout design, and Table 3 summarises sensor and preprocessing choices.

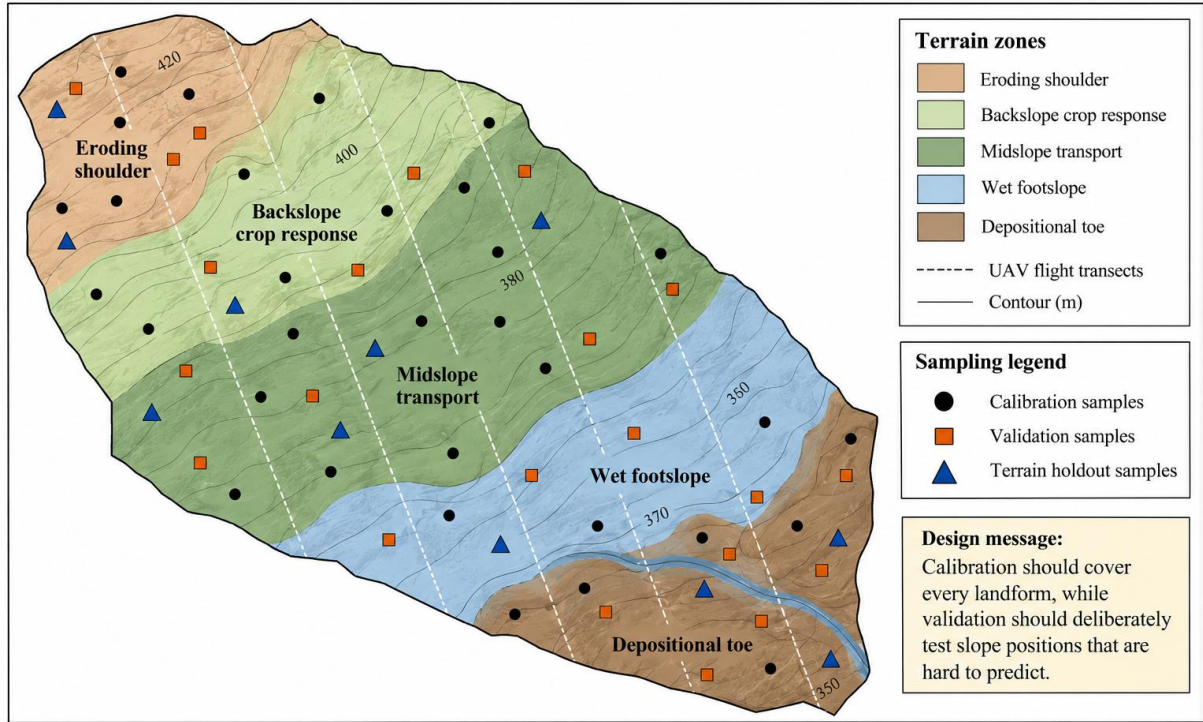


Figure 4. Terrain-stratified sample allocation and validation holdout design for UAV SOC mapping.

Table 3. Sensor and preprocessing choices for variable terrain.

Choice	Strength	Terrain sensitivity	Recommended use	Key caution
RGB or soil colour	Low cost, high spatial detail, intuitive relation with SOM.	Strongly affected by moisture, residue, roughness and illumination.	Bare cropland under controlled surface conditions.	Requires local calibration and careful logging of surface condition.
Multispectral	Red-edge, NIR and vegetation indices support crop and soil proxies.	Aspect, crop stage and wetness influence indices.	Bare soil, crop-mediated SOC and precision agriculture.	Indices may reflect vegetation stress instead of SOC.

Choice	Strength	Terrain sensitivity	Recommended use	Key caution
Hyperspectral	Many narrow bands support feature selection and derivative preprocessing.	Sensitive to noise, calibration and soil-mineral interference.	Heterogeneous soils where subtle spectral features matter.	Higher cost and processing load; transfer is not automatic.
LiDAR	Captures elevation, roughness, canopy height and terrain structure.	Highly useful where terrain or canopy controls SOC.	Forest, wetland, gully and slope-position studies.	Indirect SOC pathway needs strong field validation.
Satellite plus UAV	Combines temporal depth with local spatial detail.	Coarser pixels mix landform positions.	Scaling field models and choosing sampling windows.	Resolution mismatch must be handled explicitly.

7. Modelling strategies for terrain-aware UAV SOC maps

Model choice in UAV-SOC studies has moved from simple linear regression towards a mix of linear, nonlinear, ensemble and hybrid geostatistical approaches. PLSR remains useful for high-dimensional spectral data because it copes with collinearity and fits naturally with soil spectroscopy (Wold et al., 2001). Support vector regression can perform well with limited samples and nonlinear kernels (Cortes & Vapnik, 1995). Random forest is widely used because it handles nonlinear relationships and mixed covariates and provides variable importance (Breiman, 2001). XGBoost often does well where interactions are strong and data are sufficient (Chen & Guestrin, 2016). Neural networks can extract complex patterns but need more care when samples are few. Across the reviewed studies, the best model depended on context (Biney et al., 2023; El Jamaoui et al., 2024; He et al., 2025; Matinfar et al., 2021; Qi et al., 2025).

Random forest appears often because it balances accuracy, robustness and interpretability in a practical way. El Jamaoui et al. (2024) reported strong RF performance for semi-arid SOC prediction from UAV multispectral variables and soil indices. Qi et al. (2025) found RF best in two tobacco fields and XGBoost best in the other two, so model ranking changed even within one crop and region. Song and Zhang (2026) identified RF as the best model for UAV hyperspectral SOC estimation across heterogeneous farmland, and Tripathi et al. (2024) found RF with UAS data more accurate than the Sentinel-2A alternatives at their Indian site. RF is therefore a dependable baseline, but it should be tested and not simply assumed.

XGBoost is useful where predictor interactions are strong. Biney et al. (2023) found extreme gradient boosting among the strongest models once bare-soil UAV bands, spectral indices and terrain attributes were merged. He et al. (2025) reported that XGBoost outperformed RF and SVM for SOC prediction in all three *Spartina alterniflora* classes, with topographic variables making a substantial contribution. Its advantage probably comes from fitting interactions among spectral, terrain and vegetation-structure features. The weakness is that high apparent accuracy can hide site-specific relationships when external validation is weak.

SVM and SVR remain important for small and moderate datasets. Cutting et al. (2024) found that SVR gave a lower validation error than RF in their intra-field study when multivariate spectral and topographic predictors were combined, and Ding et al. (2023) obtained acceptable SVM performance for Tibetan thermo-erosion gullies. SVM results are sensitive to kernel choice, scaling and hyperparameters, but the method can work well when samples are limited and the response surface is nonlinear. A terrain-aware review should therefore avoid presenting ensemble tree models as the default answer for every dataset.

Hybrid models join deterministic covariates with the spatial structure of the residuals (Goovaerts, 1997; Hengl et al., 2018). Matinfar et al. (2021) compared PLSR, RF, quantile regression forest, Cubist, SoLIM, RF-ordinary kriging and QRF-ordinary kriging. The hybrid RF-OK model performed best, and combining geomorphometric with remote-sensing covariates outperformed remote sensing alone. This is relevant to UAV studies because high-resolution maps can still show residual spatial structure after spectral and terrain covariates have been used. Kriging the residuals may improve a map, but it should be done with care when sampling is sparse or when clustered sampling inflates spatial autocorrelation.

Feature engineering should express process and not only maximise correlation. Spectral indices such as NDVI, EVI, SAVI, OSAVI, NDRE and red-edge combinations, together with soil colour metrics, derivative spectra and texture measures, can improve prediction (Huete, 1988; Tucker, 1979). Terrain features such as TPI, TWI, slope, aspect, roughness, elevation, relief amplitude and flow accumulation should be chosen according to the expected SOC mechanism. LiDAR variables such as the canopy height model and DEM-derived features are valuable where vegetation structure and terrain shape control SOC patterns. The strongest models in the reviewed studies usually merged covariate families: UAV bands with indices and terrain (Biney et al., 2023), reflectance with TPI (Wehrhan & Sommer, 2021), vegetation indices with LiDAR (Chen et al., 2025), and spectral with topographic variables (Cutting et al., 2024; Zou et al., 2024).

Validation design is the main safeguard against overstatement. Random splits can give optimistic results when neighbouring points share soil, management and illumination conditions (Meyer et al., 2018; Roberts et al., 2017). Leave-one-out cross-validation is useful for small datasets but may not test spatial transfer. External validation on a neighbouring field, another gully, another terrain class or a later flight date is more informative.

Heil et al. (2022) tested transfer to an adjacent field, Ding et al. (2023) used independent samples from other thermo-erosion gullies, and Cutting et al. (2024) compared single-date, multivariate, topographic and combined predictor sets. Studies intended for operational carbon assessment should report both local fit and transfer performance (Table 4).

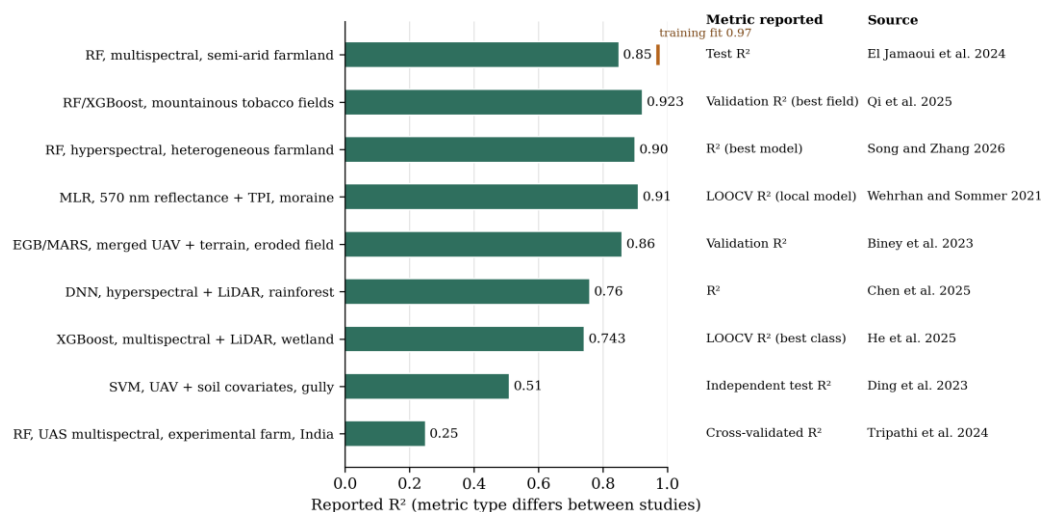
Table 4. Validation and uncertainty checklist for UAV SOC studies in variable terrain.

Validation element	Minimum expectation	Stronger practice	Reason it matters
Sampling support	State depth, compositing method and laboratory method.	Report bulk density and stock conversion when mapping stocks.	Prevents confusion between SOC concentration and SOC stock.
Spatial validation	Hold out random samples.	Use spatial blocks or terrain-class holdouts.	Tests whether models interpolate across landforms.
External validation	Use a separate test subset.	Use another field, date, gully or slope class.	Shows whether the model transfers beyond local calibration.
Surface condition	Describe crop cover and bare-soil state.	Record residue, moisture, roughness, rainfall history and shadow by terrain class.	Separates the SOC signal from transient surface effects.
Uncertainty map	Report RMSE and R^2 .	Map uncertainty or prediction intervals and extrapolation zones.	Shows where management decisions are risky.
Model interpretation	Report feature importance.	Interpret feature importance in the light of soil processes and terrain.	Avoids mistaking statistical importance for causal SOC control.

8. Methodology comparison and recommended use

A comparison of methods should start with the observation pathway, not the name of the algorithm. Bare-soil studies assess a relatively direct spectral expression of SOC, whereas crop-mediated, wetland and forest studies assess indirect signals carried by vegetation, water status or canopy structure. This difference explains why a method that performs well in one study may not transfer to another terrain setting. The most useful method in practice is the one that matches the dominant source of signal and still holds up when validated outside the easiest calibration points.

The highest local results among the reviewed UAV-SOC studies came mainly from ensemble tree methods paired with well-chosen UAV covariates. El Jamaoui et al. (2024) reported RF values of $R^2 = 0.97$, RMSE = 1.41 and RPIQ = 2.48 in a semi-arid multispectral drone study; the R^2 of 0.97 described the training fit, and the test R^2 was about 0.85. Qi et al. (2025) reported field-specific RF and XGBoost models with validation R^2 above 0.90 in mountainous tobacco fields. Song and Zhang (2026) reported RF as the best hyperspectral model, with $R^2 = 0.90$ and RPD = 3.11 after spectral transformation. Biney et al. (2023) obtained $R^2_{\text{val}} = 0.86$ for EGB and MARS when bare-soil UAV bands, spectral indices and high-resolution terrain attributes were merged. These results favour RF and XGBoost or EGB as first-choice methods when nonlinear spectral-terrain interactions are expected (Figure 5).



Values are study-specific; sensor, terrain, sample size and validation design differ, so the bars are not a direct ranking.

Figure 5. Study-specific performance examples and practical model selection for UAV-based SOC assessment. Values are taken from the cited studies and differ in metric type (training, validation, cross-

validated or independent test R^2), sensor and terrain; they should not be read as a direct ranking. Sources: El Jamaoui et al. (2024), Qi et al. (2025), Song and Zhang (2026), Wehrhan and Sommer (2021), Biney et al. (2023), Chen et al. (2025), He et al. (2025), Ding et al. (2023) and Tripathi et al. (2024).

PLSR and other linear methods remain useful, though in a narrower role. PLSR is appropriate when hyperspectral or laboratory spectral predictors are numerous and highly collinear, and it gives an interpretable baseline for spectroscopy-led work. In the erosion-prone UAV study of Biney et al. (2023), however, PLSR was weaker than the nonlinear models. SVM and SVR are more competitive when samples are few and the relationship is nonlinear. Ding et al. (2023) found SVM effective for thermo-erosion gullies despite a moderate R^2 , and Cutting et al. (2024) found SVR useful when spectral predictors were combined with topography.

Deep learning, LiDAR fusion and hybrid geostatistical models are best regarded as problem-specific tools. Chen et al. (2025) used UAV hyperspectral and LiDAR features with a deep neural network in tropical rainforest, where the canopy prevented direct soil observation. He et al. (2025) found XGBoost most effective for SOC under *Spartina alterniflora* when multispectral and LiDAR data were grouped by vegetation state. Matinfar et al. (2021) showed that hybrid RF-ordinary kriging with geomorphometric covariates can improve field-scale SOC mapping when residual spatial structure remains. These methods earn their place when terrain or canopy creates a structured residual pattern that a spectral model alone cannot represent.

Our recommendations are therefore conditional. For bare or nearly bare eroding cropland, a merged dataset of UAV bands, indices and terrain attributes modelled with RF or XGBoost is the leading option. For heterogeneous hyperspectral farmland, RF with spectral transformation and feature selection is the strongest starting point. For small datasets, SVM or SVR should be kept as a benchmark because they can perform well with limited samples. For wetlands and forests, LiDAR fusion usually matters more than the choice between RF and XGBoost, since the SOC signal is carried mainly by structure, elevation, water and vegetation. For carbon monitoring or high-stakes accounting, the best method is not simply the model with the highest R^2 ; it is the model supported by laboratory calibration, spatially explicit validation and an uncertainty layer that remains stable across terrain classes (Heil et al., 2022; Matinfar et al., 2021; Tripathi et al., 2024). Figure 6 summarises this logic, and Table 5 compares the method families.

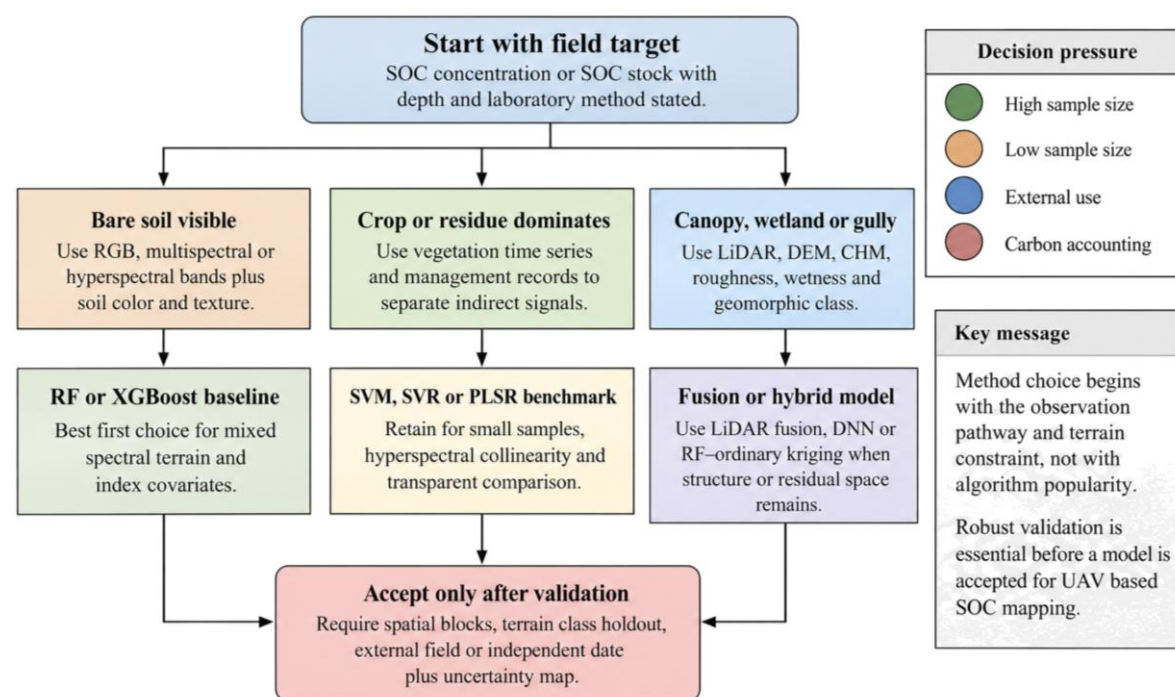


Figure 6. Method selection framework for terrain-aware UAV SOC mapping.

Table 5. Methodology comparison and recommended use for UAV-based SOC assessment.

Method family	Best terrain or data situation	Representative evidence	Main limitation	Recommendation
PLSR and linear models	High-dimensional spectra, controlled bare-soil conditions and baseline comparison.	PLSR handled spectral collinearity but was weaker than nonlinear models in Biney et al. (2023).	Often misses nonlinear terrain, moisture, residue and canopy interactions.	Use as an interpretable benchmark, not as the only model in complex terrain.

Method family	Best terrain or data situation	Representative evidence	Main limitation	Recommendation
SVM or SVR	Small to moderate sample sets, nonlinear relations and sharply disturbed terrain.	SVM was effective for thermo-erosion gullies (Ding et al., 2023); SVR performed well with topography (Cutting et al., 2024).	Sensitive to kernel choice, scaling and hyperparameter tuning.	Good option when samples are limited and terrain classes are explicit.
Random forest	Mixed spectral, terrain, texture and soil covariates with nonlinear responses.	Training $R^2 = 0.97$ (test ≈ 0.85) (El Jamaoui et al., 2024); $R^2 = 0.90$ (Song & Zhang, 2026); UAS RF better than Sentinel-2A (Tripathi et al., 2024).	Can look strong under local random splits while transferring poorly.	Treat as the strongest general baseline for UAV-SOC studies.
XGBoost, EGB and MARS	Strong interactions among bands, indices, terrain attributes, wetness and vegetation state.	EGB and MARS $R^2_{val} = 0.86$ (Biney et al., 2023); XGBoost validation R^2 up to 0.923 (Qi et al., 2025).	High accuracy can hide overfitting if validation is weak.	Use for high-performance mapping with spatial or terrain-class validation.
DNN with LiDAR or hyperspectral data	Forest, wetland and canopy-obstructed systems where SOC is inferred indirectly.	UAV hyperspectral and LiDAR features with DNN in tropical rainforest (Chen et al., 2025).	Needs more samples, careful feature selection and cautious interpretation.	Best where structure, canopy or terrain carries much of the SOC signal.
Hybrid machine learning and kriging	Fields with spatial autocorrelation remaining after covariates are modelled.	RF-ordinary kriging with geomorphometric covariates (Matinfar et al., 2021).	Kriged residuals can mislead under sparse or clustered sampling.	Use for final map refinement only after residual structure has been tested.

9. Transferability and uncertainty

Transferability is the main unresolved problem in UAV-based SOC assessment. A model can be accurate within a field because it has learned a local relationship among soil colour, residue, moisture, management and SOC. The same model may fail in a field with a different parent material, carbonate content, residue load, slope aspect or illumination. Heil et al. (2022) showed promising transfer between neighbouring fields but stressed that UAV data collection and processing are not standardised enough to assume broad portability. Wehrhan and Sommer (2021) found that cross-field application preserved the spatial SOC pattern better than the absolute SOC level. These results point to a practical distinction between mapping relative within-field variation and estimating absolute SOC content for carbon accounting.

Uncertainty should be mapped and not only summarised. A single R^2 or RMSE value cannot show where a map is unreliable. Variable terrain produces spatially uneven error because some landform positions are under-sampled, shadowed, wetter, rougher or more vegetated than others. A useful UAV-SOC product should present prediction intervals or uncertainty classes alongside the SOC map. Ensemble spread, quantile regression forest, bootstrapped models, spatial cross-validation and independent validation points can all support uncertainty assessment (Meinshausen, 2006; Roberts et al., 2017; Wadoux et al., 2020). The map should also flag extrapolation areas, such as landform positions absent from the calibration set or spectral values outside the training range (Meyer & Pebesma, 2021).

Scale mismatch adds further uncertainty. Laboratory SOC is measured on a sample with a particular depth and compositing protocol, whereas UAV pixels represent surface reflectance, crop canopy or terrain at centimetre to metre scale. SOC stocks require bulk density and depth, but many UAV studies predict concentration. The mismatch is manageable when the target is stated clearly; it becomes a problem when concentration maps are read as stock maps without accounting for depth, bulk density, stone content and soil redistribution (Batjes, 2016; Jobbágy & Jackson, 2000). Lian et al. (2022) addressed SOC stocks in a desertified landscape, while most cropland studies dealt with topsoil SOC concentration or SOM. Reviews and future studies should keep these targets apart.

A second scale issue concerns the difference between image resolution and decision resolution. A UAV orthomosaic may have centimetre pixels, but a farmer, watershed manager or carbon programme rarely acts at that support. Management usually takes place by zone, strip, plot, terrace, gully unit or field. A terrain-aware SOC workflow should therefore aggregate predictions to units that match the intended decision, while keeping the fine-resolution map for diagnosis. Doing so avoids a false sense of precision and helps to reconcile UAV products with laboratory sampling, satellite records and carbon accounting frameworks. Heil et al. (2022),

Tripathi et al. (2024) and Song and Zhang (2026) show how high-resolution SOC products can inform field decisions; the next step is to report how pixel-scale uncertainty changes once predictions are aggregated to management zones.

Temporal transfer matters as much as spatial transfer. SOC changes slowly, but the UAV signal can change quickly with moisture, crop stage, residue, tillage and illumination. A model calibrated in one bare-soil window may not hold after rainfall or a different tillage operation. Time-series approaches, such as the UAS imagery used by Guo et al. (2020), reduce dependence on a single date by capturing vegetation development, and the multivariate Sentinel-2 models combined with terrain by Cutting et al. (2024) point in the same direction. For UAVs, repeated flights can separate persistent SOC-related patterns from transient surface effects, although they increase the processing load and demand careful radiometric consistency.

The most promising way forward is a tiered validation protocol. The first tier tests internal model behaviour with cross-validation. The second uses spatial blocking or terrain-class holdouts to evaluate interpolation across landforms. The third tests an independent field, date or landform, and the fourth links map error to its management consequences. A map used for variable-rate amendment can tolerate a different level of uncertainty from one used for carbon-credit reporting, and terrain-aware UAV-SOC assessment should make this distinction explicit.

10. Implications for soil management and carbon monitoring

Terrain-aware UAV SOC maps can support precision agriculture by identifying zones that need different management (Maes & Steppe, 2019; Mulla, 2013). Low-SOC eroded shoulders may need residue retention, cover crops, reduced tillage, contour practices, manure or compost and erosion-control structures. Depositional footslopes may call for different nutrient management because they often accumulate fine material and organic matter. Wet hollows may need drainage management or crops suited to the hydrological constraints. Read together with terrain, SOC maps become diagnostic maps of process as well as fertility maps.

The same maps can make sampling more efficient. An initial UAV survey can reveal spectral and terrain strata, so that later laboratory samples are placed where they reduce uncertainty most. This is valuable in smallholder and resource-limited settings where dense sampling is expensive. Tripathi et al. (2024) demonstrated the potential of UAS data for SOC prediction under Indian agricultural conditions, and national assessments have shown that SOC stocks in Indian soils vary widely between physiographic regions and have set out priorities for soil carbon management (Bhattacharyya et al., 2000, 2009). A terrain-aware UAV workflow could help to target sampling in regions where soil-testing capacity is limited and within-field variability is high.

For carbon monitoring, UAV maps are most credible when paired with repeatable protocols. Carbon projects need defensible baselines, resampling designs and uncertainty estimates (Minasny et al., 2017; Paustian et al., 2016; Smith, 2004). UAVs can improve the spatial allocation of samples and reveal management zones, but they cannot replace laboratory measurement for SOC stocks. They work best as a spatial intensification tool: they guide where to sample and how to stratify estimates, and they help detect areas where erosion or deposition may violate simple assumptions about vertical SOC change. This role is consistent with the wider spectroscopy and digital soil mapping literature (Angelopoulou et al., 2019; Mulder et al., 2011; Viscarra Rossel et al., 2016).

The Indian context strengthens the practical case for terrain-aware UAV workflows. Tripathi et al. (2024) showed that a RedEdge UAS dataset predicted SOC better than Sentinel-2A at their site, although accuracy still left room for improvement. In small, intensively managed fields with monsoon-driven moisture changes, variable residue and local relief, UAV data should make soil testing more efficient by directing samples towards terrain and management contrasts.

Semi-arid systems need their own interpretation. In dry agricultural regions SOC is often low, vegetation cover is patchy, and soil brightness is strongly affected by carbonates, salts, iron oxides, gravel, crusting and moisture pulses after rain. El Jamaoui et al. (2024) and El-Jamaoui et al. (2025) showed that UAV multispectral indices and machine learning can predict SOC in semi-arid fields, but such models should be interpreted with local soil chemistry and surface condition in mind. The work of Bartmiński et al. (2024) reinforces this caution for carbonate-rich soils. In semi-arid terrain the most reliable UAV workflow may combine bare-soil imagery, soil mineral information, terrain position and a short weather record rather than rely on vegetation indices alone.

Variable terrain also affects how maps should be communicated. A map that labels SOC as low, medium or high without terrain context can lead to poor decisions, because a low-SOC convex slope and a low-SOC sandy flat may require different interventions. We therefore recommend delivering UAV-SOC maps with a terrain interpretation layer showing erosion risk, likelihood of deposition, wetness class, canopy obstruction and a confidence category.

11. Research agenda

Future research should move from single-field demonstrations to transferable, terrain-aware protocols. New studies should compare bare-soil, crop-mediated, LiDAR, hyperspectral and multispectral pathways along the same terrain gradient. They should report failure modes as well as the best model, including wet areas, shadowed slopes, residue-rich patches, carbonate soils, canopy-covered sites and extrapolated landforms. Such reporting would make UAV-SOC assessment far more useful for operational deployment.

Standardised reporting is needed. Each study should state the SOC target, depth, laboratory method, sampling support, flight date, time since rainfall, surface condition, sensor calibration, ground control, covariate resolution, validation design and uncertainty method. Many of the reviewed studies report several of these elements, but seldom in a form that allows comparison. A shared reporting template would raise the value of future reviews and meta-analyses.

Open benchmark datasets would speed up progress. The field has many convincing local demonstrations but few datasets that let independent groups compare sensors, preprocessing choices, terrain variables and validation schemes under the same conditions. A useful benchmark would include UAV imagery, calibration records, ground control, DSM or LiDAR layers, field photographs, rainfall and soil-moisture notes, laboratory SOC with depth and bulk density, and a terrain-stratified validation design. It should also include difficult cases such as eroded slopes, residue-rich surfaces, wet hollows, shaded terrain, carbonate soils and canopy-obstructed plots (Table 6).

Table 6. Research agenda for UAV-based SOC assessment in variable terrain.

Gap	Why it limits current studies	Recommended response	Expected benefit
Transferability across terrain	Local models often learn site-specific colour, moisture, residue or crop response.	Test models across independent fields, dates and landform classes.	Clear separation of robust SOC signals from local artefacts.
Standardising surface condition	Moisture and residue can dominate reflectance.	Develop field protocols for rainfall interval, residue cover, roughness and bare-soil quality.	Better comparability among UAV studies.
SOC concentration versus stock	Many maps predict concentration but are read as stocks.	Measure bulk density, depth, stones and erosion-deposition context.	More defensible carbon accounting.
Canopy-obstructed terrain	Optical UAV data cannot observe soil under forest or dense wetland vegetation.	Fuse LiDAR structure, vegetation indices, terrain and targeted soil sampling.	SOC mapping in ecosystems excluded from bare-soil workflows.
Communicating uncertainty	Single accuracy values hide terrain-specific errors.	Publish uncertainty layers and terrain-specific error summaries.	More responsible use in management and carbon markets.
Cost-effective deployment	Hyperspectral and LiDAR data can be expensive.	Compare low-cost RGB or multispectral workflows with higher-end sensors by terrain class.	Practical protocols for farmers and regional programmes.

Terrain-aware transfer learning and model updating deserve attention, although this review does not treat complex algorithms as a substitute for field knowledge. Regional spectral libraries, small local calibration sets, spiking and memory-based learning may help to move models between fields while preserving local accuracy (Brown et al., 2006; Shepherd & Walsh, 2002; Stevens et al., 2013). Dai et al. (2025) showed the value of memory-based learning for predicting SOC fractions from a regional VNIR library in tropical cropland, and the same principle may support UAV workflows when local samples are scarce. The challenge is to keep transfer methods interpretable enough for soil management decisions.

The most promising research direction is sensor fusion guided by process. Hyperspectral data capture subtle spectral variation, multispectral cameras offer cheaper operational coverage, RGB imagery provides colour and texture, LiDAR records terrain and vegetation structure, and satellite time series supply seasonal context (Adão et al., 2017; Manfreda et al., 2018). The most effective UAV-SOC system will not deploy every sensor everywhere. It will use the smallest combination of sensors that resolves the dominant terrain problem: bare-soil colour in tilled fields, crop response in low-relief cropland, LiDAR structure under canopy, wetness and elevation in hydrologically complex terrain, and erosion-deposition metrics in sloping fields.

Table 7 places the UAV-SOC studies reviewed here within the wider methodological literature on spectroscopy, digital soil mapping, terrain analysis, UAV photogrammetry, machine learning, geostatistics and carbon monitoring. It keeps the review focused on UAV assessment while showing the literature behind each methodological choice.

Table 7. Citation map supporting the review.

Evidence domain	Studies cited in the review	Role in the article
UAV-based and field-scale SOC and SOM mapping studies	(Biney et al., 2023; Chen et al., 2025; Ding et al., 2023; El Jamaoui et al., 2024; El-Jamaoui et al., 2025; Guo et al., 2020; He et al., 2025; Heil et al., 2022; Lian et al., 2022; Qi et al., 2025; Song & Zhang, 2026; Takata et al., 2023; Tripathi et al., 2024; Wehrhan & Sommer, 2021); satellite or airborne comparison studies (Cutting et al., 2024; Matinfar et al., 2021; Zou et al., 2024)	Defines the direct evidence base for UAV imagery, UAV LiDAR, bare-soil mapping, crop-mediated inference, wetlands, forests, gullies and terrain-specific SOC prediction.
Soil spectroscopy, spectral libraries and spectral indices	(Angelopoulou et al., 2019; Bartholomeus et al., 2008; Bartmiński et al., 2024; Baumgardner et al., 1985; Ben-Dor & Banin, 1995; Ben-Dor et al., 2009; Brown et al., 2006; Castaldi et al., 2019; Dai et al., 2025; Henderson et al., 1992; Huete, 1988; Nocita et al., 2015; Peng et al., 2013; Reeves, 2010; Shepherd & Walsh, 2002; Soriano-Disla et al., 2014; Stenberg et al., 2010; Stevens et al., 2013; Tucker, 1979; Viscarra Rossel & Behrens, 2010; Viscarra Rossel et al., 2006, 2016)	Supports the interpretation of soil colour, organic matter absorption, red-edge and NIR indices, moisture and iron-oxide effects, carbonate interference and local spectral calibration.
Digital soil mapping and soil-terrain modelling	(Arrouays et al., 2014; Behrens et al., 2018; Florinsky, 2016; Gessler et al., 1995; Hengl et al., 2017, 2018; Jenny, 1941; McBratney et al., 2003; Minasny & McBratney, 2016; Moore et al., 1991, 1993; Mulder et al., 2011; Poggio et al., 2021; Scull et al., 2003; Tarboton, 1997; Wilson & Gallant, 2000)	Frames the terrain-explicit design around soil-forming factors, DEM derivatives, topographic wetness, landform position, process covariates and map-scale prediction.
UAV acquisition, photogrammetry and radiometric workflow	(Aasen et al., 2015; Adão et al., 2017; Anderson & Gaston, 2013; Colomina & Molina, 2014; Honkavaara et al., 2013; James & Robson, 2012; Maes & Steppe, 2019; Manfreda et al., 2018; Mulla, 2013; Nex & Remondino, 2014; Torres-Sánchez et al., 2014; Turner et al., 2012; Watts et al., 2012; Westoby et al., 2012; Zhang & Kovacs, 2012)	Supports the workflow elements on flight planning, ground control, structure-from-motion reconstruction, camera calibration, high-resolution orthomosaics and UAV use in precision agriculture.
Machine learning, geostatistics and validation	(Breiman, 2001; Chen & Guestrin, 2016; Cortes & Vapnik, 1995; Cressie, 1993; Friedman, 2001; Goovaerts, 1997; Hastie et al., 2009; Kuhn, 2008; Kuhn & Johnson, 2013; Liaw & Wiener, 2002; Meinshausen, 2006; Meyer & Pebesma, 2021; Meyer et al., 2018; Pebesma, 2004; Roberts et al., 2017; Wadoux et al., 2020; Wold et al., 2001)	Supports the comparison of RF, XGBoost, SVM, PLSR, DNN, quantile forests, hybrid kriging, external validation, area of applicability and spatial cross-validation.
SOC stocks, erosion and carbon monitoring	(Batjes, 1996, 2016; Berhe et al., 2007; Bhattacharyya et al., 2000, 2009; Doetterl et al., 2016; Jobbágy & Jackson, 2000; Lal, 2004; Minasny et al., 2017; Paustian et al., 2016; Smith, 2004; Stockmann et al., 2013; Van Oost et al., 2007)	Links UAV-SOC mapping to stock estimation, vertical carbon distribution, erosion and deposition, soil carbon sequestration, monitoring uncertainty and land-management relevance.

12. CONCLUSION

UAV-based SOC assessment has progressed from experimental field imagery to a practical form of high-resolution digital soil mapping. The reviewed studies show that multispectral, hyperspectral, RGB, LiDAR and satellite-assisted workflows can estimate SOC or SOM with useful accuracy when laboratory measurements, radiometric control and terrain covariates are combined carefully (Biney et al., 2023; Chen et al., 2025; Guo et al., 2020; Heil et al., 2022; Song & Zhang, 2026). The main conclusion is that UAV data are most reliable when the sensing pathway is chosen from the soil process rather than from whichever sensors happen to be available.

Complex terrain is an active factor in UAV SOC mapping, not a background condition. Convex shoulders, depositional footslopes, gullies, wet hollows, forested slopes and coastal wetlands differ in erosion, deposition, drainage, vegetation input, canopy obstruction and surface moisture. These differences alter the true SOC pattern as well as the reflectance, texture, structural and vegetation signals that prediction models use. A high R^2 therefore means little unless validation demonstrates transfer across terrain positions (Heil et al., 2022; Meyer & Pebesma, 2021; Roberts et al., 2017; Wehrhan & Sommer, 2021).

The methodological conclusion is conditional but practical. Work on bare or nearly bare eroding cropland should begin with UAV bands, indices, texture and terrain attributes tested with RF or XGBoost (Biney et al., 2023; Qi et al., 2025). Hyperspectral farmland studies should begin with spectral transformation, feature selection and RF (Song & Zhang, 2026). Small or sharply disturbed datasets should keep SVM or SVR as benchmarks (Cutting et al., 2024; Ding et al., 2023). Forests, wetlands and other canopy-obstructed terrain often require LiDAR fusion and structure-aware models (Chen et al., 2025; He et al., 2025). Hybrid machine learning and kriging are useful when residual spatial structure remains after the covariates have explained the main terrain signal (Matinfar et al., 2021).

For management and carbon monitoring, UAV SOC products should be treated as decision layers and not as replacements for laboratory SOC measurement. The strongest workflow uses UAV and terrain data to design sampling, laboratory SOC to calibrate and validate models, and uncertainty maps to identify risky field or carbon-accounting decisions. Such a map can locate eroded low-carbon zones, depositional accumulation areas, wetness-controlled uncertainty and landform positions that need resampling before management or carbon-credit decisions are made.

Future reviews and field studies should report SOC depth, sampling support, terrain class, surface condition, sensor calibration, validation design and uncertainty in a comparable format. The core contribution of this review is to reframe UAV-based SOC assessment as a terrain-aware workflow in which field sampling, image acquisition, covariate extraction, model choice and map interpretation are all guided by soil redistribution processes. This framing matters most in complex terrain, where the same UAV signal may indicate organic carbon, moisture, residue, vegetation response, exposed subsoil or transported sediment depending on landform position.

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Author contributions

Arunpandi P conceptualised the review, collected and analysed the literature, prepared the figures and tables and wrote the original draft. Jagadeeswaran R supervised the work and reviewed and edited the manuscript. Muthumanickam D, Sendhilvel V and Anandhi V contributed to the interpretation of the literature and reviewed and edited the manuscript. All authors read and approved of the final manuscript.

Conflict of interest

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

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