Light, algorithms and liability: A legal-optical risk index for AI-driven crop sensing under EU law

Global Journal of Social Sciences Studies
Vol. 12, No. 2, 65-77, 2026.
e-ISSN: 2518-0614



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ABSTRACT

Optical sensors carried aboard satellites, drones, and farm robots feed data into AI algorithms, which advise or apply plant treatments using fiber-optic and wireless communication. This research investigates the means by which the legal risk associated with such systems can be quantified prior to their implementation in European agriculture. Combining a doctrinal analysis of six layers of EU law (the AI Act as amended by the Digital Omnibus on AI, the GDPR, the Data Act, the Machinery Regulation, the revised Product Liability Directive and the NIS 2 Directive, along with the EU drone legislation) with the Quantification of Everything (Q.E.) method, the study develops the Legal-Optical Risk Index (LORI), with six weighted components, one of which is calculated physically from the ground sampling distance (GSD) of the camera. When applied to four illustrative crop production use cases, LORI ranges from 0.128 for the satellite-based vegetation index (NDVI) advisory system to 0.893 for the autonomous laser weed removal robot. The ranking of the scenarios proved robust in all 10,000 Monte Carlo weight variations. Legal risk in optical-AI agriculture is mostly governed by two engineering design decisions, namely, image resolution and machine autonomy, not by the AI model itself. Farmers, agricultural cooperatives, and providers of agricultural technology may employ LORI during sensor selection for the purpose of determining the optimal height of the sensor above the crops, image resolution, and the level of human oversight while mitigating legal risk.

Keywords: *Agricultural law, Artificial intelligence, EU AI Act, Multispectral imaging, Precision agriculture, Quantification of Everything (Q.E.).*

DOI: 10.55284/gjss.v12i2.2018
Citation | Challoumis, C., Mavrommatis, K., & Constantinou, A. (2026). Light, algorithms and liability: A legal-optical risk index for AI-driven crop sensing under EU law. *Global Journal of Social Sciences Studies, 12*(2), 65–77.
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Funding: This research was funded by the Special Account for Research Funds (ELKE), University of West Attica, Greece.
Institutional Review Board Statement: Not applicable.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: C.C. developed the research concept, designed the Q.E.-based index, and prepared the manuscript; C.C. and K.M. performed the analysis of optical engineering and networking; C.C. and A.C. performed the analysis of EU law on AI and liability. All authors reviewed and approved the final manuscript.
History: Received: 1 September 2026/ Revised: 23 October 2026/ Accepted: 10 November 2026/ Published: 16 November 2026
Publisher: Online Science Publishing

Highlights of this paper

- The Legal-Optical Risk Index (LORI) is a link between the optical characteristics of cameras and EU laws applicable in the realm of AI-assisted crop sensing.
- Image resolution finer than 2 cm per pixel and autonomous actuation of machinery are the two factors that contribute most to legal risk.
- After the 2026 Digital Omnibus on AI, AI in agricultural machinery is regulated primarily through the Machinery Regulation.

1. INTRODUCTION

Farming practice in Europe increasingly relies on optical methods. Satellite imaging allows canopy state to be assessed, drones with multispectral cameras detect plant diseases, and robotized spraying or weeding machines guided by cameras are gaining popularity (Fountas et al., 2020; Kamilaris & Prenafeta-Boldú, 2018; Liakos, Busato, Moshou, Pearson, & Bochtis, 2018; Mahlein, 2016; Mulla, 2013; Weiss, Jacob, & Duveiller, 2020). In each of these examples, an AI model translates reflected light into agronomic decisions.

Academic literature on these technologies from agronomic and engineering perspectives is plentiful and keeps expanding (Sparrow & Howard, 2021; Wolfert, Ge, Verdouw, & Bogaardt, 2017). Precision technologies promise reduced inputs and a smaller environmental footprint (Basso & Antle, 2020; Finger, Swinton, El Benni, & Walter, 2019); their adoption, however, varies (Lowenberg-DeBoer & Erickson, 2019). By contrast, their legal status has not been researched extensively enough, despite the fact that several regimes of EU law apply to them (European Parliament and Council of the European Union, 2016, 2023b, 2024c).

The social sciences' approach to the study of digital agriculture is mainly concerned with data ownership and the imbalance of power between farmers and platforms (Klerkx, Jakku, & Labarthe, 2019; Ryan, 2020; Wiseman, Sanderson, Zhang, & Jakku, 2019), while hardly engaging with the optics of the sensors used. However, the physical parameters of a sensor, including its altitude, focal length, pixel size, and spectral bands, determine whether a photo contains an identifiable individual and thus whether it counts as personal data under the relevant laws.

Apart from the legal implications, the use of AI in agriculture also brings economic consequences. Recent empirical papers report a positive correlation between AI adoption or the capacity to adopt AI technology and macroeconomic indicators in Greece and Cyprus (Challoumis & Eriotis, 2025). The cost of compliance with the regulations concerning agricultural AI is thus important to countries where small-scale farming is common, as in the Mediterranean region.

In order to fill the gap, this paper makes three contributions. First, it identifies six layers of EU law applicable to the optical-AI pipeline in crop production, taking into account the Digital Omnibus on AI adopted in 2026 (European Parliament and Council of the European Union, 2026). Second, it formulates the Legal-Optical Risk Index (LORI) based on the Quantification of Everything (Q.E.) methodology, whereby legal notions are expressed in numerical form (Challoumis, 2026). Third, it applies the LORI to four illustrative scenarios of optical-AI application in agriculture.

The research question posed is: *which design options of an AI-driven optical crop sensing system contribute the most to its legal exposure in the context of EU laws, and to what extent?*

2. OPTICAL SENSING AND AI IN CROP PRODUCTION

2.1. Platforms and Spectral Ranges

Optical crop sensing occurs across four different spatial scales (Weiss et al., 2020). Satellites like Sentinel-2, for instance, offer 13 spectral bands with a spatial resolution ranging from 10 to 60 meters and a revisit period of around five days (Drusch et al., 2012). Unmanned aerial vehicles (UAVs) may employ RGB, multispectral or

thermal cameras that achieve a spatial resolution at the centimeter level and can be operated on demand (Maes & Steppe, 2019). Ground robots and tractor cameras capture crop images at the leaf level, with a spatial resolution at the sub-millimeter scale (Fountas et al., 2020). Furthermore, fiber-optic cables not only serve to transfer sensor information to cloud AI services but can also act as temperature and strain sensors themselves.

Most agronomic indices use the difference between red light absorbed by chlorophyll and near-infrared (NIR) light reflected from leaves. The Normalized Difference Vegetation Index (NDVI), defined in Equation 1, is a classic case (Rouse, Haas, Schell, & Deering, 1974):

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (1)$$

where ρ stands for the surface reflectance in the given spectral band. Hyperspectral images contain hundreds of bands, which makes it possible to identify stress and disease at an early stage (Lu, Dao, Liu, He, & Shang, 2020; Mahlein, 2016).

2.2. The Resolution Equation

The ground sampling distance (GSD) of a nadir-looking camera depends on three engineering factors (Equation 2):

$$GSD = \frac{H \cdot p}{f} \quad (2)$$

where H is the flight altitude above the surface, p is the pixel size of the sensor, and f is the focal length of the camera. The GSD is the connecting point of optics and legislation in this paper: it determines whether the face of a person, a license plate of a car or a garden is identifiable, and therefore whether the image contains personal data.

2.3. From Pixels to Decisions

Convolutional neural networks accurately classify plant diseases on leaf images in controlled environments (Mohanty, Hughes, & Salathé, 2016) and the use of deep learning is already widespread for weed detection, yield prediction, and phenotyping (Kamilaris & Prenafeta-Boldú, 2018; Liakos et al., 2018). The main point from the legal perspective is not the structure of the model, but its use in the decision-making process:

1. Advisory – the model gives a map or alert and a human makes the decision.
2. Prescriptive – the model creates the variable-rate prescription file, which a human approves and uploads to the machine.
3. Actuating – the model operates sprayer nozzles, a laser or a robotic arm in real time.

The further one goes down the list, the more AI is integrated into the machine safety function and human review of every decision becomes impossible (Fountas et al., 2020; Sparrow & Howard, 2021). Automation of field operations also creates redistributive issues as seasonal laborers are replaced by robots. Redistributive policy regimes such as economocracy have been put forward to address automation-induced unemployment (Challoumis, 2025).

3. THE EU LEGAL FRAMEWORK FOR OPTICAL-AI FARMING SYSTEMS

There is no EU instrument that specifically deals with agricultural AI. Instead, there are six layers of EU law, each activated by a different trait of the system (Table 1).

Table 1. EU instruments activated by optical-AI crop sensing and their technical trigger.

Instrument	Technical trigger in crop sensing	Main obligation or consequence
AI Act, Reg. (EU) 2024/1689, as amended by Reg. (EU) 2026/1744 (European Parliament and Council of the European Union, 2024c, 2026)	AI used as a safety component of a product covered by Union harmonization law (Art. 6(1), Annex I)	High-risk requirements: risk management, data governance, logging, human oversight; Annex I obligations apply from 2 August 2028
GDPR, Reg. (EU) 2016/679 (European Parliament and Council of the European Union, 2016)	Image resolution sufficient to identify a person, vehicle or dwelling	Lawful basis, transparency, data minimization; impact assessment for systematic monitoring
Data Act, Reg. (EU) 2023/2854 (European Parliament and Council of the European Union, 2023b)	Connected tractor, robot or sensor generating product data	Farmer's right to access and share data; limits on the manufacturer's own use
Machinery Reg. (EU) 2023/1230 (European Parliament and Council of the European Union, 2023a)	Self-evolving, machine-learning behavior ensuring safety functions of machinery	Essential health and safety requirements; third-party conformity assessment for Annex I, Part A categories
Product Liability Dir. (EU) 2024/2853 (European Parliament and Council of the European Union, 2024a)	Software, including AI systems and their updates, treated as a product	Strict liability for defects; disclosure duties and presumptions that ease the claimant's burden
NIS 2 Dir. (EU) 2022/2555 and Impl. Reg. (EU) 2019/947 (European Commission, 2019; European Parliament and Council of the European Union, 2022)	Networked operation; UAV flights	Cyber-risk management for covered entities; UAV operating categories and operator duties

3.1. The AI Act after the Digital Omnibus: Autonomy, Not Agriculture, Triggers High Risk

Agriculture is not on the list of stand-alone high-risk fields in Annex III to the AI Act (European Parliament and Council of the European Union, 2024c; Veale & Zuiderveen Borgesius, 2021). As a result, an application that detects crop diseases and offers advice will normally fall outside the high-risk category. However, if AI is performing a safety function in any product that is regulated by the Union harmonization legislation in Annex I, then such AI becomes high-risk under Article 6(1).

Regulation (EU) 2026/1744, the Digital Omnibus on AI, has modified both the timing and the route of those obligations (European Parliament and Council of the European Union, 2026). The high-risk obligations will now apply from 2 December 2027 for Annex III systems and from 2 August 2028 for Annex I systems. The Machinery Regulation has been transferred to Section B of Annex I, meaning that health and safety requirements for AI embedded in machinery will now be incorporated into the Machinery Regulation through delegated acts. In the case of an autonomous weeding robot, the route will be modified but not the substance of obligations. Machinery with embedded machine learning systems providing safety functions is included in Annex I, Part A, of the Machinery Regulation and is subject to third-party conformity assessment once that regulation applies on 14 January 2027 (European Parliament and Council of the European Union, 2023a).

3.2. The GDPR: Resolution Decides Applicability

Personal data are any information relating to an identified or identifiable natural person (Art. 4(1) GDPR) (European Parliament and Council of the European Union, 2016). While a satellite image with 10-m pixels cannot identify anyone, a drone image with sub-centimeter GSD can show faces, license plates, and private gardens next to the field, and the surveillance and privacy risks associated with civil drones have long been known (Finn & Wright, 2012). In other words, the question "is the GDPR applicable?" partially translates into the optical question "what is the GSD?". Commercial drone operators cannot use the household exemption, while systematic observation of

neighboring property might require a data protection impact assessment. In addition, compliance has an economic side, which has been considered in the case of Greece (Challoumis, Eriotis, Vasiliou, & Mavrommatis, 2026). For farms with small margins, avoiding unnecessary processing of personal data makes sense both economically and legally.

3.3. The Data Act and Data Control

Since 12 September 2025, users of connected products, including farmers operating smart tractors and robots, have had the right to obtain access to the data generated by their equipment and to share the data with third parties (European Parliament and Council of the European Union, 2023b). This right complements the voluntary EU Code of Conduct on Agricultural Data Sharing (Copa-Cogeca et al., 2018) and helps rectify the long-standing asymmetry between farmers and technology providers (Ryan, 2020; Wiseman et al., 2019).

3.4. Liability and Cybersecurity

The revised Product Liability Directive will apply to products placed on the market after 9 December 2026 and will treat software, including AI, as a product. The Directive will also cover defects that result from software updates or from the absence of security updates (European Parliament and Council of the European Union, 2024a). For a farmer whose crops are destroyed because of a misclassifying sprayer, this shifts the practical route to compensation toward the system's manufacturer. Nevertheless, evidentiary problems persist when one cannot reconstruct the output of a deep model (Wachter, Mittelstadt, & Russell, 2018). Network dependency adds yet another aspect: AI models running in the cloud depend on rural backhaul, increasingly a fiber connection under the Gigabit Infrastructure Act (European Parliament and Council of the European Union, 2024b), so outages and intrusions are agronomic threats (European Parliament and Council of the European Union, 2022).

4. MATERIALS AND METHODS

4.1. The Q.E. Approach

The Q.E. approach represents qualitative legal triggers as bounded values that can be combined, aggregated and analyzed for sensitivity (Challoumis, 2026). The score x_{jk} of system j with respect to the k-th legal dimension takes values in $[0, 1]$, where 0 corresponds to non-applicability of the instrument and 1 corresponds to its strictest regime. The Legal-Optical Risk Index is the weighted sum shown in Equation 3:

$$LORI_j = \sum_{k=1}^{6} w_k x_{jk} \quad (3)$$

with $\Sigma w_k = 1$, so that $0 \leq LORI_j \leq 1$.

4.2. Dimensions, Weights and Scoring Rules

Table 2 provides a summary of the six legal dimensions, their weights and scoring rules.

Table 2. LORI dimensions, weights and scoring criteria.

k	Dimension	Weight w_k	Scoring rule for x_{jk}
1	Identifiability of persons (GDPR)	0.20	$x_{j1} = \min(1, g*/GSD_j)$, with $g* = 0.02$ m (Equation 4)
2	Decision autonomy (Human oversight)	0.20	Advisory 0.25; prescriptive 0.50; actuating 1.00
3	Safety-function status (AI Act Art. 6(1); Machinery Reg.)	0.20	None 0; machine-coupled but human-gated 0.50; autonomous safety function 1.00
4	Data-access and sharing duties (Data Act)	0.15	Third-party service 0.25; connected product 0.50; connected product with several data holders 0.75
5	Explainability gap (product liability)	0.15	Index-based 0.10; shallow model 0.30; deep model 0.70
6	Connectivity and cyber dependence (NIS 2, network law)	0.10	Batch download 0.25; cloud-dependent 0.50; real-time networked control 0.75

Dimension 1 comes directly from physical measures instead of being based on expert opinion (Equation 4):

$$x_{j1} = min(1, \frac{g^*}{GSD_j}) \quad (4)$$

The threshold $g* = 2$ cm per pixel is a scale at or below which one may start to recognize such details as a person standing, a license plate of a car, or a garden in nadir imagery. A GSD equal to or finer than $g*$ receives a score of 1 and coarser imagery receives a proportionally smaller score. Dimensions 2 and 3, as well as dimension 1, have the greatest weight (0.20) since these dimensions define whether the GDPR and the high-risk regime apply at all. The explainability gap reflects the difficulty of explaining a deep model's outputs, even with post-hoc explanation methods (Lundberg & Lee, 2017; Wachter et al., 2018).

4.3. Sensitivity Analysis

In order to verify that the results are not dependent on the selected weights, the weight vector was sampled 10,000 times from a Dirichlet distribution whose mean equals the weights in Table 2 (concentration 50, random seed 42). In each draw, the four scenarios were re-scored and re-ranked. The 5th and 95th percentiles of each scenario's LORI values define its 90% interval. All computations were made in Python using the NumPy package; the corresponding code is provided in Appendix A.

4.4. Scenarios

Four scenarios represent the spectrum of current practices on European farms for both field crop production and horticulture. Camera parameters are typical of available commercial sensor types; they are illustrative and do not describe any real-world device.

- S1, satellite advisory: Sentinel-2 NDVI zoning delivered as a web map (GSD 10 m).
- S2, multispectral UAV prescription: UAV at 60 m height above the ground, pixel pitch 3.75 µm and focal length 5.74 mm; the output is a variable-rate nitrogen prescription confirmed by the farmer.
- S3, RGB UAV disease detection: UAV at 30 m height above the ground, pixel pitch 2.4 µm and focal length 8.8 mm; a deep learning classifier identifies diseased regions and creates a prescription for spraying.
- S4, autonomous laser weeding robot: Cameras at 1 m height above the ground, pixel pitch 3.45 µm and focal length 8 mm; a deep learning model detects the weeds and activates the laser with no human decision-making.

5. RESULTS

LORI increases sevenfold across the considered scenarios, from 0.128 (S1) to 0.893 (S4) (Table 3).

Table 3. Dimension scores, GSD and LORI for the four scenarios.

Scenario	GSD	x_1	x_2	x_3	x_4	x_5	x_6	LORI	90% interval
S4 Laser-weeding robot	0.43 mm	1.00	1.00	1.00	0.75	0.70	0.75	0.893	0.861–0.922
S3 RGB UAV disease detection	0.82 cm	1.00	0.50	0.50	0.50	0.70	0.50	0.630	0.587–0.680
S2 Multispectral UAV prescription	3.92 cm	0.51	0.50	0.50	0.50	0.30	0.50	0.472	0.454–0.487
S1 Satellite NDVI advisory	10 m	0.002	0.25	0.00	0.25	0.10	0.25	0.128	0.101–0.155

Note: x_1–x_6 are the dimension scores from Table 2; LORI is calculated using Equation 3; the 90% interval corresponds to the 5th–95th percentile range of 10,000 draws of the Dirichlet weights.

5.1. Resolution Is the First Legal Threshold

Going from S2 to S3, LORI increases by 0.158, of which 0.098 comes only from identifiability. Flying the S2 drone at 30 m would bring its GSD down to 1.96 cm and fully activate the GDPR. On the other hand, flying the S2 drone at 120 m would make its GSD equal to 7.8 cm and reduce its identifiability score from 0.51 to 0.26, thereby decreasing LORI from 0.472 to 0.421. Nitrogen zoning is unlikely to need higher resolution, as management zones are several meters wide.

5.2. Autonomy Is the Second, and Largest, Threshold

Transitioning from S3 to S4 adds 0.263 – the biggest single increase. It is caused by both autonomy (+0.10) and safety-function status (+0.10). Once the robot's vision model fires the laser without human review, the machine becomes subject to the machinery safety regulation and, via Annex I of the AI Act, to AI-specific regulation. The higher resolution of S4 contributes nothing to LORI because S3 had already achieved the maximum identifiability score.

5.3. Robustness

The ranking S4 > S3 > S2 > S1 was preserved in all 10,000 draws. Since the 90% intervals do not overlap, the ranking does not depend on the particular choice of weights. In each 90% interval, the deviation of the index from its central value does not exceed 0.05.

6. DISCUSSION

The results show that the legal exposure of optical-AI crop sensing is mostly determined by two technical features – image resolution and machine autonomy. This allows compliance to be treated as a design task that can be addressed by agronomists and engineers before involving lawyers.

6.1. Implications for Farmers and Cooperatives

Three simple guidelines can be derived from the analysis of the results. First, farmers should select the coarsest image resolution acceptable from the agronomic perspective; nitrogen zoning and vigor mapping rarely need imagery more detailed than 5 cm (Maes & Steppe, 2019; Weiss et al., 2020). Second, farmers should keep a human approval step in cases where full machine autonomy would yield little benefit, since the farmer's review of the prescription file keeps the system out of the safety-function category. Third, when purchasing connected machinery,

farmers should secure their Data Act rights in the procurement contract, thus ensuring that the field data remain available to advisory services (Copa-Cogeca et al., 2018; European Parliament and Council of the European Union, 2023b).

6.2. Implications for Agri-Tech Suppliers

For autonomous systems like S4, the safety regime becomes unavoidable, and design work has to focus on the technical parameters that can still be tuned. On-board image processing that discards non-crop pixels lowers the personal-data footprint even in the case of sub-millimeter GSD. Logging and explaining the decisions, e.g., via a feature attribution map for each laser shot (Lundberg & Lee, 2017), narrows the explainability gap and limits evidentiary exposure under the revised Product Liability Directive (European Parliament and Council of the European Union, 2024a).

6.3. Implications for Regulators

Excluding agriculture from the application of Annex III of the AI Act is justified in the case of advisory tools. However, it leaves a gray area for prescriptive systems like S3, in which the machine output gets to the field via a human operator who may lack the means to verify it. Sectoral guidance on meaningful human oversight of agricultural prescriptions and on reducing the amount of drone imagery around human dwellings would reduce uncertainties for small farms. Delegated acts that will introduce the AI-specific requirements into the Machinery Regulation by August 2028 (European Parliament and Council of the European Union, 2023a, 2026) are expected to become the main regulatory tool for agricultural robots. Gigabit roll-out in rural areas under the Gigabit Infrastructure Act (European Parliament and Council of the European Union, 2024b) will lead to the proliferation of cloud-based systems, making network resilience a factor in food production resilience.

6.4. Limitations

LORI is a screening tool, not a legal opinion. The weights it uses are based on a doctrinal judgment that has been tested for sensitivity but has not yet been confirmed by case law due to the lack of litigation on agricultural AI. The scenarios used in this paper are illustrative, as is the 2 cm threshold for imagery identifiability: oblique imaging, image enhancement, and data linkage can make even coarse imagery identifying. The analysis was carried out within the framework of EU law, and national transposition of the Product Liability Directive and of NIS 2, as well as national drone regulation, may change individual scores. Further work should include calibration of the weights through expert elicitation with agronomists, data protection authorities, and insurers, as well as validation of LORI on real deployments.

7. CONCLUSIONS

AI-driven optical sensors are revolutionizing agriculture, and EU regulation now covers every stage of the optical-AI pipeline, from pixels to lasers. This paper applied doctrinal analysis together with the Q.E. approach to develop a Legal-Optical Risk Index and found that legal exposure increases sevenfold from satellite advisory services to autonomous field robots. Two critical thresholds stand out: one for image resolution finer than roughly 2 cm, at which privacy laws become relevant, and one for autonomous actuation, beyond which machinery laws apply and, through them, AI rules. Both are design decisions. Thus, farmers, suppliers, and regulators are in a position to mitigate legal risk in the design phase, retaining agricultural utility and lowering compliance costs. Calibrating the index against actual implementations is the obvious follow-up step.

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Appendix A. Python code for the legal-optical risk index

The Python 3 script in Listing A1, which uses the NumPy library, reproduces the values in Table 3, the 90% intervals and the robustness check reported in Section 5.3, and the flying-height comparison in Section 5.1. Listing A2 shows its output. The code is protected by the following notice:

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Listing A1. Python code for the LORI computation and the sensitivity analysis.

```
# ============================================================
# Legal-Optical Risk Index (LORI) for AI-driven optical crop sensing
# Reproduces Table 3, the 90% intervals (Section 5.3) and the
# flying-height comparison for scenario S2 (Section 5.1).
#
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# ============================================================
import numpy as np
from collections import Counter

G_STAR = 0.02  # identifiability threshold g* in meters per pixel (Table 2)

# Weights w_k (Table 2): identifiability, autonomy, safety function,
# data-access duties, explainability gap, connectivity/cyber dependence
W = np.array([0.20, 0.20, 0.20, 0.15, 0.15, 0.10])


def gsd(height, pixel_pitch, focal_length):
    """Ground sampling distance in meters, Equation 2: GSD = H * p / f."""
    return height * pixel_pitch / focal_length
```

```
def identifiability(gsd_m):
    """Dimension 1, Equation 4: x_j1 = min(1, g* / GSD_j)."""
    return min(1.0, G_STAR / gsd_m)


def lori(x, w=W):
    """Equation 3: LORI_j = sum over k of w_k * x_jk."""
    return float(np.dot(w, x))


# Ground sampling distance of each scenario (Section 4.4)
GSD = {
    "S1": 10.0,                      # Sentinel-2 imagery, 10 m
    "S2": gsd(60.0, 3.75e-6, 5.74e-3),   # multispectral UAV at 60 m
    "S3": gsd(30.0, 2.40e-6, 8.80e-3),   # RGB UAV at 30 m
    "S4": gsd(1.0, 3.45e-6, 8.00e-3),    # laser-weeding robot, camera at 1 m
}

# Scores x_j2 ... x_j6 from the scoring rules in Table 2
OTHER_SCORES = {
    "S1": [0.25, 0.00, 0.25, 0.10, 0.25],
    "S2": [0.50, 0.50, 0.50, 0.30, 0.50],
    "S3": [0.50, 0.50, 0.50, 0.70, 0.50],
    "S4": [1.00, 1.00, 0.75, 0.70, 0.75],
}

X = {s: np.array([identifiability(GSD[s])] + OTHER_SCORES[s]) for s in GSD}
ORDER = ["S4", "S3", "S2", "S1"]

# --- Table 3 ----------------------------------------------------------
print("Scenario   GSD (m)      x1      LORI")
for s in ORDER:
    print(f"{s:9s}  {GSD[s]:9.5f}   {X[s][0]:6.3f}   {lori(X[s]):.3f}")

# --- Sensitivity analysis (Section 4.3) -------------------------------
N_DRAWS, CONCENTRATION, SEED = 10_000, 50, 42
rng = np.random.default_rng(SEED)
values = {s: [] for s in X}
rankings = Counter()
for _ in range(N_DRAWS):
    w = rng.dirichlet(W * CONCENTRATION)
```

```
    scores = {s: lori(X[s], w) for s in X}
    for s in X:
        values[s].append(scores[s])
    rankings[" > ".join(sorted(scores, key=scores.get, reverse=True))] += 1

print("\n90% intervals (5th-95th percentiles of 10,000 weight draws)")
for s in ORDER:
    low, high = np.percentile(values[s], [5, 95])
    print(f"{s}: {low:.3f}-{high:.3f}")
print("Rankings:", dict(rankings))

# --- Flying-height comparison for scenario S2 (Section 5.1) ----------------
for height in (30.0, 60.0, 120.0):
    g = gsd(height, 3.75e-6, 5.74e-3)
    x = X["S2"].copy()
    x[0] = identifiability(g)
    print(f"S2 at {height:5.1f} m: GSD = {100 * g:.2f} cm, "
          f"x1 = {x[0]:.3f}, LORI = {lori(x):.3f}")
```

Listing A2. Output of the script in Listing A1.

```
Scenario   GSD (m)     x1     LORI
S4         0.00043    1.000   0.893
S3         0.00818    1.000   0.630
S2         0.03920    0.510   0.472
S1        10.00000    0.002   0.128

90% intervals (5th-95th percentiles of 10,000 weight draws)
S4: 0.861-0.922
S3: 0.587-0.680
S2: 0.454-0.487
S1: 0.101-0.155
Rankings: {'S4 > S3 > S2 > S1': 10000}
S2 at  30.0 m: GSD = 1.96 cm, x1 = 1.000, LORI = 0.570
S2 at  60.0 m: GSD = 3.92 cm, x1 = 0.510, LORI = 0.472
S2 at 120.0 m: GSD = 7.84 cm, x1 = 0.255, LORI = 0.421
```

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