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Editorial

Editorial: From Precision Detection to Measurement Fidelity—Emerging Directions in Laser Detection and Remote Sensing

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The performance of a laser detection system is commonly summarized by a limited set of instrumental figures of merit, including detection range, sensitivity, spatial or spectral resolution, ranging precision, and temporal response. These specifications remain indispensable for instrument characterization, but none alone determine the fidelity of the retrieved physical quantity. In remote sensing, the detected signal represents only one stage of a longer measurement chain. The transmitted field evolves along the propagation path and interacts with molecules, aerosols, surfaces, or engineered targets before the return is transformed by receiver optics, detector response, calibration, and retrieval [1,2]. The practical limit of a laser sensing system is therefore determined not simply by the weakest detectable signal, but by how faithfully the physical information encoded in that signal can be retained and interpreted. For quantitative remote sensing, uncertainty is consequently not an afterthought to instrument performance but an integral part of interpreting the retrieved quantity [3]. The contributions to the second edition of the Special Issue "Laser as a Detection: From Spectral Imaging to Lidar for Remote Sensing Applications" address this problem at different stages of the measurement chain, spanning atmospheric propagation, Lidar inversion and wind sensing, time-resolved detection, three-dimensional reconstruction, multimodal imaging, and stand-off spectroscopy.

Atmospheric propagation provides perhaps the most direct illustration of why this distinction matters. Refractive-index fluctuations do not simply reduce the mean transmitted power; they modify beam spreading, wander, irradiance fluctuations, phase coherence, and the spatial distribution of energy at the receiver or target [4]. Their influence is path-dependent and becomes particularly important for oblique propagation through an atmosphere whose turbulence strength varies strongly with height. Hu et al. [5] characterize this variability observationally using temperature-fluctuation measurements of near-surface Cn^2 in the Nanjing area. Their results reveal pronounced temporal and vertical structure, reinforcing the inadequacy of representing a realistic propagation environment by a single nominal turbulence strength. Ye et al. [6] approach the complementary engineering problem. Using a large wave-optics database, they quantify the coupled dependence of slant-path beam spreading on initial beam quality, propagation distance, elevation angle, turbulence, and tracking jitter, and use a compact feedforward neural network as a surrogate for one coefficient of the resulting scaling relation. Their broader significance lies not in any individual turbulence statistic or scaling coefficient, but in demonstrating how the propagation medium enters directly into system performance. For atmospheric

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laser systems, the atmosphere cannot be reduced to an attenuation term in the link budget; its refractive structure is part of the effective optical system. The underlying turbulence physics is well-established [4], but the two contributions illustrate how that physics must be carried into both environmental characterization and engineering prediction.

Once the return is acquired, the dominant limitation may shift from propagation to inference. Elastic-backscatter Lidar is a classic example because aerosol extinction is not observed directly but inferred from a range-resolved backscatter signal under assumptions about the relationship between extinction and backscatter and about conditions at a reference range. The Klett and Fernald solutions established the practical foundations for such inversions [7,8], while retrieval theory more generally emphasizes that an atmospheric product is conditioned jointly by the observations, the forward model, and the information introduced to make the inverse problem solvable [9]. Klett explicitly examined the stability of the inversion to perturbations in the signal, the assumed extinction–backscatter relationship, and the boundary value. Zhao et al. [10] revisit the boundary-value problem for horizontal Fernald inversion. Rather than estimating the boundary from a manually identified homogeneous interval using a slope method, they exploit the divergence behavior of forward integration to constrain an alternative boundary value. Simulations indicate greater robustness to atmospheric inhomogeneity and random noise, and the method was further applied to horizontal scanning observations [10]. Treating this choice as a purely numerical detail obscures its physical consequence. When the retrieved extinction field is materially conditioned by the prescribed boundary, the boundary specification belongs to the inference chain rather than to numerical bookkeeping alone.

Direct-detection Doppler wind Lidar makes this coupling particularly explicit. The molecular double-edge technique provides a means of converting small Doppler frequency shifts into differential intensity changes [11], and the subsequent 355 nm demonstration by Gentry et al. showed that molecular wind profiles could be retrieved from approximately 1.8 to 35 km and compared favorably with coincident rawinsondes [12]. The development of ADM-Aeolus extended direct-detection Doppler wind Lidar from terrestrial demonstrations to a spaceborne observing concept in which laser stability, spectral discrimination, calibration, atmospheric scattering, retrieval, and validation all became mission-level concerns [13,14]. Within this broader trajectory, Yang et al. [15] examine a different platform constraint: a compact Rayleigh Doppler Lidar intended for prospective operation on a stratospheric airship. Their 532 nm system combines a fixed-cavity dual-channel Fabry–Perot discriminator with non-mechanical switching between orthogonal lines of sight. Laboratory experiments in controlled Mie- and Rayleigh-dominated conditions reported measurement uncertainty below 0.34 m/s at a range resolution of 0.48 m [15]. These results should not be conflated with demonstrated stratospheric performance, which remains a future deployment problem. The relevant advance is therefore not miniaturization alone, but the attempt to preserve spectral-discrimination performance within a strongly platform-constrained architecture.

The measurement-chain perspective is equally relevant to time-of-flight and three-dimensional sensing. In direct time-of-flight imaging, depth is inferred from photon arrival time, making timing resolution, detector statistics, background rejection, electronic nonlinearity, and signal processing integral to the recovered range product [16]. Single-photon time-of-flight imaging has demonstrated kilometer-scale three-dimensional measurements even when the mean signal return falls below one detected photon per pixel, provided that photon detection and reconstruction are treated jointly [17]. Chen et al. [18] address the timing front end through an in-pixel time-to-digital converter for dToF imaging. Their post-layout results report a TDC resolution of 156 ps and an absolute ranging accuracy of approximately 2.5 cm, with a phase-locked-loop architecture introduced to reduce sensitiv-

ity to process, voltage, and temperature variations [18]. At a later point in the information chain, Duan [19] addresses distortions already expressed in structured-light Lidar point clouds, combining decision-tree classification with adaptive least-mean-square filtering to distinguish and compensate distorted regions [19]. The two studies operate at very different levels of the system architecture, yet together they make an important point: three-dimensional fidelity is determined cumulatively across timing, optical formation, calibration, and reconstruction. Improvements at one stage cannot, in general, compensate for information lost at another.

A further transition concerns the number and physical diversity of observables available to the retrieval or recognition problem. Multisensor fusion has long sought to exploit complementary measurements [20], and hyperspectral–Lidar studies have shown how spectral information and three-dimensional structure can jointly improve scene characterization [21]. Yin et al. [22] extend this principle by combining hyperspectral, polarimetric, and Lidar depth information under few-shot conditions. Their framework constructs modality-specific physical feature mappings and uses multi-scale hierarchical optimization to combine information across the three modalities [22]. This is conceptually more important than simply increasing the number of image channels. Multimodal sensing becomes informative only when the added observables provide non-redundant physical sensitivity to the scene. Spectral reflectance, polarization response, and depth encode different target properties; their joint use is therefore valuable only if those distinctions survive registration, calibration, and fusion. The central problem is not dimensionality itself, but whether physically complementary observables remain complementary after processing.

The progression from remote detection toward identification becomes still clearer in laser spectroscopy. Stand-off laser absorption spectroscopy encompasses several approaches for recovering chemically informative signatures remotely, including tunable absorption and differential techniques [23]. For biological aerosols, however, the distinction between detection and identification is particularly important. Elastic scattering can reveal the presence and distribution of an anomalous aerosol cloud, whereas laser-induced fluorescence provides additional biological discrimination but remains affected by spectral overlap, environmental interferents, and biological variability [24]. Paukovčeková and Tatar [25] examine how mid-infrared spectroscopy may add a further level of chemical specificity through vibrational signatures associated with biomolecular constituents. Their review considers differential scattering, circular intensity differential scattering, tunable differential absorption approaches, quantum-cascade lasers, and dual-comb spectroscopy, while also emphasizing atmospheric attenuation, particle-size effects, biological variability, and signal interpretation as continuing limitations [25]. Thus, moving from detecting the presence of an aerosol cloud to identifying its composition shifts the limiting problem from signal detectability toward molecular specificity, interference rejection, and spectral interpretation.

Taken together, these studies suggest that the frontier of laser detection cannot be represented by a single axis of increasing range, resolution, power, or sensitivity. Each remains important, but the benefit of improving one subsystem diminishes when uncertainty elsewhere in the chain becomes dominant. A more useful question is therefore end-to-end: how faithfully can the information generated by the laser–medium interaction be carried through propagation, detection, calibration, inversion, and interpretation? This perspective also changes the design problem. Propagation modeling should inform the transmitter and receiver design; detector response should be carried explicitly into retrieval development; calibration and sensitivity analysis should accompany rather than follow algorithm development; and multimodal systems should be configured around the complementary physics of their observables. The design problem consequently shifts from optimizing isolated

components to co-designing the complete measurement chain. For atmospheric Lidar in particular, uncertainty should increasingly accompany the retrieved product rather than appear only as an error estimate added after the retrieval [3,9].

Data-driven methods will undoubtedly become more deeply embedded in this chain, but their scientific value depends strongly on how they are introduced. In Earth-system science, hybrid approaches combining process understanding with data-driven learning have been advocated as a route toward improved physical consistency and generalization [26]. Physics-informed machine learning extends this principle by embedding governing equations, constraints, or other prior physical knowledge within learning frameworks [27]. Several contributions in this Special Issue already place learning or statistical methods at different points in the sensing process, including atmospheric-propagation parameterization [6], point-cloud correction [19], and multimodal information fusion [22]. The more consequential direction is unlikely to be unrestricted replacement of physically based retrieval with black-box prediction. A more useful role is to combine data-driven flexibility with propagation physics, instrument response, calibration information, and explicit uncertainty. This distinction is particularly important for quantitative Lidar, because predictive accuracy within a training distribution does not by itself establish the physical validity of a retrieval outside it.

The second edition of this Special Issue consequently captures a field in which atmospheric optics, laser engineering, spectroscopy, detector electronics, computational imaging, and inference are increasingly parts of the same measurement problem. Such convergence does not diminish the need for disciplinary physics; it makes such physics more consequential. A compact Lidar is valuable only if the reduction in size and complexity preserves calibration and retrieval performance. A more sophisticated algorithm is useful only if its output can still be related quantitatively to the measured signal and its uncertainty. A multimodal instrument is advantageous only when the added observables contribute independent physical information. Higher sensitivity matters only when the additional detected signal can be interpreted quantitatively. The established strengths of laser detection—directionality, temporal precision, spectral selectivity, coherence, and controlled interaction with matter—remain fundamental. What is changing is the level at which these capabilities must now be integrated.

The next generation of laser remote-sensing systems will therefore be judged not only by how far, how fast, or how precisely they detect, but by whether they provide quantitative, uncertainty-characterized, and physically interpretable information under realistic observing conditions. The contributions assembled in this Special Issue address different parts of that objective, from characterization of the propagation environment and improved Lidar inversion to platform-oriented wind sensing, precision timing, three-dimensional correction, multimodal fusion, and composition-sensitive spectroscopy. Viewed together, they support a broader conclusion: source, propagation, interaction, detection, calibration, inversion, and interpretation are best treated not as independent technical modules, but as coupled elements of a single measurement system.

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