Estimating location specific water column properties from remote sensing signals via machine learning

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Inherent Optical Properties (IOPs) such as spectral absorption and scattering of the water column and its dissolved and particulate constituents indicate the quality, biological, and biogeochemical processes [7] of the water. IOPs are insensitive to changes in the light field and by monitoring IOPs help sustainable management of *inland* and *ocean* water resources and interpret climate change effects to some extent. For instance, phytoplankton absorption relates to chlorophyll concentration (Chl) at a particular region or season [8], and particle backscattering relates to particulate carbon content [9]. In the early days of ocean optics, measuring *in situ* IOPs was challenging compared to radiometric variables, e.g., *remotely*-sensed upwelling and downwelling irradiances, which depend both on the medium and the geometry of the radiance distribution. They are called Apparent Optical Properties (AOPs) and thus become popular to describe water bodies. Moreover, remote sensing is a viable solution for water monitoring as its wide coverage in the spatial areas at frequent intervals.

Remote sensing reflectance, R_{rs} , (i.e. an AOP) is typically calculated as the ratio of water-leaving radiance to downwelling irradiance just above the air-sea interface. We then derive IOPs by solving an appropriate *forward model* that explicitly relates bio-optical relationships (e.g. via IOPs) to radiative-transfer processes (e.g. observed R_{rs})—a.k.a. inverse modeling [5]. An example is the radiative transfer equation [1], an analytical model for water constituents—e.g. total suspended matter (TSM), Colored Dissolved Organic Matter (CDOM), and phytoplankton—and remote sensing signals: the irradiance reflectance, and the remote sensing reflectance, R_{rs} . It links IOPs with AOPs of the water column for both deep and optically deep coastal water, and captures the attenuation of light due to water constituents [2,3]. In coastal water, water constituents are heterogeneously distributed, and hence, parameterized by region-specific variables. However, such forward modeling methods can be computationally intensive, conceptually complex—requires expert domain knowledge, and limited by any assumptions associated with measurements [5].

A promising approach, the focus of this study, is to derive IOPs and water constituents such as CDOM and phytoplankton from remote sensing signals via statistical or machine learning methods. Without assuming a predefined model, they directly relate the parameters of interest to the remote sensing signals by training with known samples. People employed methods such as multiple linear regression [11], principal component regression [12], support vector regression [14], neural networks [13], and gene expression programming [10] successfully to

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this problem [5]. We plan to study the performance of (generic) data-driven machine learning methods such as deep learning, trained on the ground truth data from a specific region, in comparison with the traditional forward modeling approaches.

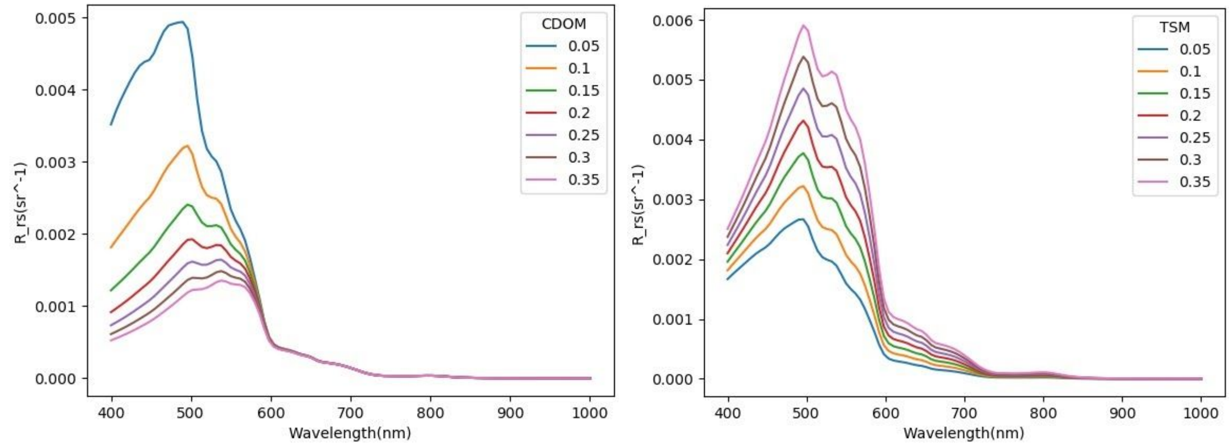

Figure 1. An exploratory study of the simulated data, based on the radiative transfer equation [1], shows values of R_{rs} (y axis) vs. different wavelengths (x axis). The left plot highlights variability in CDOM and the right plot shows variability in TSM—the colored lines.

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