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Accessible remote sensing of water

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7 | General discussion and future outlook

The aim of this thesis has been to investigate and improve accessibility and uncertainty in remote sensing and citizen science, so that these techniques can better deliver the desired improvements to cost, scale, and reproducibility of water research (Section 1.1.4). Accessibility was improved by accounting for disability in citizen science (Chapter 2) and by developing consumer cameras as low-cost instruments for remote sensing by professional and citizen scientists (Chapters 3, 4, and 6). The uncertainty in measurements by citizen scientists and measurements from consumer cameras was assessed and reduced (Chapters 2, 3, and 4), as was the uncertainty in comparing and combining data from different professional instruments (Chapter 5). Here, a general synthesis, discussion, and future outlook are provided.

The current direction of research in remote sensing of water is towards higher-dimensional data by including a wider wavelength range (UV–NIR), finer spectral sampling, and polarisation; automation; and more in-depth analysis of uncertainty and information content.

Satellite remote sensing of water has come a long way since its origins in the 1970s, when Landsat-1 data were used to map ocean currents based on a dynamic range of only 4 ADU [96]. Successive generations of satellite instruments developed by different organisations, such as the NASA Satellite Ocean Colour programme and Landsat missions and the EU/ESA Copernicus programme [85, 467], continue to provide high-resolution, high-quality data. Planned to launch in 2024, the PACE mission will further expand satellite remote sensing of water with its hyperspectral and spectropolarimetric instruments OCI, SPEXone, and HARP-2. Combined observations from these instruments will enable joint aerosol-water reflectance retrieval algorithms, improving the accuracy of both aerosol and water constituent products. Furthermore, PACE will provide insights into aerosol-water interactions, which play a key role in global biogeochemical cycles and climate change [86]. Ongoing prelaunch research includes characterisation of its instruments and capabilities [111, 112, 184], generation of synthetic data [186], and development of algorithms for data processing and analysis [185, 188, 421].

Current in-situ instrumentation development is focused on automation of sensors and data processing to enable autonomous data collection on larger scales and with greater consistency [89, 109, 117, 124, 399]. This improves the cross-validation between satellite and in-situ radiometry and makes it possible to measure high-frequency local time series. Optical measurements are being further integrated with existing networks such as Argo [80], providing additional information and improving the accuracy of retrieval algorithms [216].

These new developments will be valuable tools for studying the changes occurring in global waters. Climate change is affecting phytoplankton community compositions [42, 232, 417] and the availability of habitats for aquatic animals [468]. Similar trends are caused by pollution with nutrients, causing eutrophication and algal blooms [47], and toxins, which kill organisms and damage ecosystems [69]. Equally important to study are the resulting feedback mechanisms, such as the role of phytoplankton in carbon capture and export [469, 470]. Increased remote sensing capabilities, in particular wide spatial coverage with high-frequency observations, combined with a general increase in adoption of remote sensing by water managers and policymakers, are necessary to meet data requirements for modelling and understanding the changes occurring in waters worldwide [89, 471].

This chapter places the research described in the previous chapters into the context discussed above and in Chapter 1. Comparisons between individual results and the existing literature are presented in the discussion sections of the respective chapters, and will not be repeated here. Section 7.1 discusses our research into uncertainty characterisation and mitigation. Section 7.2 discusses accessibility and inclusion in remote sensing of water, including our studies of the Forel-Ule scale and smartphone cameras. In Section 7.3, we discuss the potential of spectropolarimetry in remote sensing of water and present initial results from a follow-up project on spectropolarimetric sensing of floating debris. Finally, Section 7.4 presents the general conclusions and recommendations to be drawn from this thesis.

7.1 Uncertainty in remote sensing of water

Formal analysis of uncertainty has historically been underutilised in the remote sensing community, to the extent that data and products were often distributed without any uncertainty estimate [88, 106]. Instead, field intercomparisons between different instruments, different algorithms, or between data and simulations have been the primary method for characterisation of uncertainty [88]. While validation with different instruments is an important step towards achieving closure (Sections 1.3.4 and 4.4.3), it is fundamentally limited. For example, data taken at slightly different times or locations and with different instruments or setups are never truly identical [409]. Uncertainty and error come from many sources, including instability and change in sensor responses, variability in targets due to waves and similar factors, shot noise, and uncertainty in sensor characterisation and calibration materials (Section 1.2.1). Advances in instrumentation, such as hyperspectral measurements or polarimetry, are pointless if measurement error and uncertainty are not appropriately characterised and minimised [144]. Improving our understanding of uncertainty is crucial to making optimal use of new platforms and technology [87, 238].

Currently, there is a strong push within the community to improve the understanding and analysis of uncertainty. For example, 2019 saw the release of IOCCG report 18, which reviewed the current state of affairs and provided numerous recommendations for future research [88]. The FRM4SOC project[22] improved the state of the art by standardising protocols, intercomparing commonly used spectroradiometers, and improving methods for uncertainty estimation and propagation [92, 97, 108, 110, 114, 120]. Additional recent research into uncertainty has included standardisation of robust comparison metrics [406, 407] and terminology [472], identification and quantification of individual contributors to the overall uncertainty budget [208, 218], and improvements to the visualisation and communication of uncertainty [278, 473]. The most important recommendation for the future is to treat uncertainty as an integral part of the measurement process, meaning uncertainty and error should be characterised as comprehensively as possible, reported as consistently as possible, and propagated as accurately as possible.

In Chapters 3 and 4, we investigated and improved the uncertainty associated with using consumer cameras as spectroradiometers. By characterising and calibrating the optical properties of several devices in the same way as professional sensors, we showed that consumer cameras can achieve an accuracy and uncertainty similar to those professional sensors, when RAW data are used. This was a major improvement on the state of the art, which until recently had been based on data in the inferior JPEG format. Our calibration methodology and data have already been adopted by other groups [412, 474, 475]. While the SPECTACLE database (Section 3.4.9) unfortunately has not materialised as intended, the associated Python

[22] Fiducial Reference Measurements for Satellite Ocean Colour, https://frm4soc.org/

package is in active development and has been published on the PyPI repository[23].

Since the original publication of Chapter 3 in 2019, the smartphone market has moved towards increasing the number of cameras per device, which further increases the amount of calibration data necessary. To facilitate collecting these data, future work will be needed to improve the accessibility of the SPECTACLE package itself, for example through a web interface. Future smartphone cameras will likely include more advanced features such as additional spectral bands and polarisation filters. The SPECTACLE methodology will need to be expanded to include calibration of the associated optical properties. Some aspects of calibration that were neglected in this thesis, such as temperature sensitivity, also require further investigation. Overall, however, we have clearly demonstrated that consumer cameras are valuable scientific instruments.

There is no single optimal method for uncertainty estimation or propagation, but any reasonable estimate is better than none. In Chapter 4, two methods for estimating radiometric uncertainty were compared, namely analytical propagation of the inter-pixel variability within one image vs. the variability in products derived from different images. The resulting uncertainty estimates were relatively close, but not identical. Notably, the analytical propagation accounted for uncertainties in calibration materials like the 18% reference grey card, which affect each measurement in the same way and thus cannot be determined from replicates. On the other hand, analytical propagation to R_{rs} is not exact (Section 4.A.3), resulting in an overestimation of the uncertainty in relative quantities like band ratios. Both methods are ultimately limited in their capacity to handle systematic errors, which are often difficult or impossible to determine and propagate statistically. These trade-offs apply to any data, and similar considerations apply to other methods for uncertainty propagation, such as Monte Carlo simulation and neural networks [88, 110]. Other considerations include the choice between absolute and relative uncertainty as well as the choice of uncertainty metric, such as coefficient of variation or interquartile range.

The importance of characterising the uncertainty in calibration materials like the 18% reference grey card extends beyond our measurements. For example, diffuse reflectance standards are often used in professional spectroradiometry to estimate E_d in the same way. The associated uncertainty has been shown to be 1%–6.5%, comparable to the overall uncertainty from other sources [435]. As recommended in Section 4.4.3, the impact of calibration material uncertainty could be reduced by characterising the materials on a large scale [400] or by issuing standard ones [394]. The same applies to the calibration methods proposed in Chapters 3 and 6.

Chapter 5 addressed a specific source of systematic error, namely incorrect spectral convolution of reflectance. The resulting error in R_{rs} was up to 5% for consumer cameras, ~1% for broad-band satellite sensors, and <1% for narrow-band satellite sensors. As the relative uncertainty in remote sensing measurements decreases below the current standards of ~5% in R_{rs} [86, 88], these systematic errors become more significant. This is especially true when they skew validation results. Spectral convolution of reflectance is now more commonly performed correctly [32, 109, 476], but other potential sources of systematic error remain to be investigated. For instance, hyperspectral data are often convolved to multispectral bands with a similar bandwidth, effectively convolving the input signal twice, while real narrow-band filters only convolve once. This discrepancy may affect the results of instrument validation studies. Future work should investigate this and other potential errors that are based on mathematical simplifications.

[23] https://pypi.org/project/pyspectacle/

The impact and communication of uncertainty in citizen science were explored in Chapter 2. Specifically, we investigated the effects of colour blindness on Forel-Ule (FU) measurements, combining current research on colour blindness in science [304] and on the FU scale in general [269, 270]. Two forms of colour blindness, deuteranopia and tritanopia, were found to significantly increase the uncertainty in simulated FU measurements by decreasing the distinguishability of colour pairs. This previously neglected factor likely affects the data quality of FU measurements and their value in validation studies. The inferred implications for inclusivity and participant motivation are discussed in Section 7.2.

Citizen science data are rarely reported with uncertainties. Based on our results, we recommend that researchers incorporate uncertainty into citizen science by having participants estimate it themselves, which requires detailed instructions [278, 315], or through post-hoc analysis. Involving citizen scientists in this way may improve public understanding of scientific uncertainty in general. This, in turn, may improve decision-making and trust in science, which the COVID-19 pandemic has shown can be somewhat lacking [477, 478].

Finally, our investigations into consumer cameras and spectropolarimetry present opportunities to decrease uncertainties in satellite and above-water remote sensing. The main source of uncertainty in satellite remote sensing of water is the atmospheric correction [208]. Spectropolarimetry provides greater information on atmospheric properties than spectroradiometry does, including aerosol particle properties, which can be used to improve the atmospheric correction. Joint retrieval algorithms for aerosol optical depth (AOD) and water-leaving radiance are in development, particularly focusing on the PACE mission [187]. The original iSPEX demonstrated the possibility for citizen scientists to measure AOD [94], and iSPEX 2 will improve the accuracy of AOD measurements through its dual-beam design and SPECTACLE-based data processing (Chapter 6). Citizen scientists could be asked through a push notification to measure AOD during a satellite overpass. Polarisation can also be used to characterise and reduce sun and sky glint [211, 240], which are major sources of uncertainty and error in above-water radiometry [120]. These possibilities can be explored with iSPEX 2 after its calibration and validation are complete (Chapter 6) or with similar instruments like groundSPEX [125]. Glint removal for spot spectroradiometers may also be improved through combined measurements with low-cost cameras, which can provide real-time wave statistics and thus improved estimates of the surface reflectivity (Chapter 4). Additionally, low-cost cameras can be deployed in the field to autonomously obtain long time series with a short cadence [479, 480].

7.2 Accessibility of water research

Science benefits from being accessible to a wide audience and inclusive of a diverse group of researchers [481, 482]. Diversity of people provides diversity of ideas, interpretations, and applications. Improving equity, diversity, and inclusion (EDI) in science has an inherent social value and increases the quality and quantity of science and its impact on society [482]. While recent years have shown significant improvements to EDI in science, including in remote sensing, there is still a long road ahead [481]. The increased focus on EDI in science is part of a wider trend towards equity in society.

Accessibility is affected not only by social factors, but also by economics. As discussed in Chapter 1, research often requires expensive equipment and specialised training. Economic disparity means that those who are most affected by environmental changes and pollution are often those with the least access to research.

Citizen science, the involvement of non-professionals in the scientific process, has experienced a boom in the last twenty years [243, 389]. This boom can largely be attributed to technological innovations such as increased internet and smartphone usage [389, 483]. Compared to traditional research conducted by professionals, citizen science provides greater data collection capabilities through crowdsourcing and increased social relevance through stakeholder participation and co-creation [95]. Citizen science is often touted as an example of inclusive science and as a method of empowerment for socially or economically disadvantaged people and nations.

However, like professional science, achieving real inclusion and equity in citizen science remains a challenge. The demographic imbalance seen in professional science is mirrored among citizen scientists, with the majority of participants belonging to socially privileged groups [484]. This imbalance is an unintentional result of the way citizen science is coordinated and used by professional researchers from a top-down perspective. In fact, the term *citizen* itself and the distinction from *professional science* influence its perception among the general public [485]. Translating the increased awareness of EDI into tangible improvements will require significant efforts in science communication, community engagement, research planning, and funding allocation [484–486]. However, the results will be worthwhile. Obtaining diverse data, for example spanning many different water bodies, requires diverse participants. Valorisation of scientific results is also improved by diversity among citizen scientists, since the participants become well-informed stakeholders, who can translate scientific knowledge into social action [294, 487]. In addition to EDI issues, professionals working with citizen scientists also need to be more aware and considerate of the citizens' desires and well-being [247, 488].

In Chapter 2, we investigated the impact of disability, specifically colour blindness, on inclusion and motivation in citizen science. Colour blindness was found to reduce the data quality in Forel-Ule (FU) measurements. Based on previous work and personal experience, we inferred that participants would be demotivated by the increased difficulty of measuring and decreased quality of results, leading to a decrease in engagement and thus inclusion. Since the FU scale represents the true colours of natural waters, it cannot be changed, and we instead made recommendations regarding data entry forms, manuals, and communication. For example, allowing participants to enter a range instead of a single value could largely mitigate the problems associated with colour blindness. Our research has led to an increased awareness of colour blindness in citizen science and the development of more inclusive techniques [489]. Future work should investigate different forms of disability and strive towards a general understanding and inclusion of disabled people in citizen science. This would likely be achieved by involving disabled people in the design of measurement protocols and manuals in a form of co-creation. In general, the quality of training materials is improved by involving participants in their development. It is often impossible for professional scientists to envision all possible problems, questions, and even unintended use cases that arise when citizens use their equipment [256, 297, 490].

In Chapters 3, 4, and 6, we investigated the use of smartphone cameras as low-cost remote sensing instruments. As discussed in Section 7.1, the quality of smartphone radiometric data was improved to a level comparable to professional sensors. This research improved upon the existing iSPEX, HydroColor, and EyeOnWater apps [94, 121, 274]. These apps have been used by professional scientists in lieu of more expensive equipment and by thousands of citizen scientists [318, 392, 393, 491]. This way, they have made remote sensing of water accessible to new audiences.

One of our aims in improving the data quality was to enable more independent research by citizens. For example, the original iSPEX could only obtain reliable data when multiple people nearby measured at the same time, during a top-down campaign [94]. The results of Chapter 4 suggest that with our improved methodology, individual citizen scientists will now be able to observe when and where they want. Additional validation for iSPEX 2 (Section 6.6.1) is ongoing, having been delayed by the COVID-19 pandemic, but we expect comparable results.

A side effect of using RAW data is the exclusion of some users whose smartphone cameras do not support RAW photography. Several potential users of iSPEX 2 have indicated that this requirement prohibits them from using the app. Unfortunately, it is up to smartphone manufacturers to enable this functionality and until that happens, these users are excluded. We have decided to fully exclude these devices rather than offer a lower-quality JPEG-based version of the app, to avoid confusion and lower-quality data. Fortunately, increased consumer demand means RAW photography is now available on all new iOS and most new Android devices, in all price ranges, so this limitation is quickly disappearing.

Smartphone science and smartphone spectroscopy are being used by thousands of people, but this is still only a minute fraction of the global population. The literature is rife with examples, proofs-of-concept, and potential use cases, and even with reviews thereof [98,143,273,345–351,492–494]. This thesis itself provides several examples. However, none have made the step towards adoption by millions of users in their daily lives. This discrepancy can be attributed to a simple lack of demand. Demonstrating a scientifically interesting use case is not enough to generate commercial interest and investment. For smartphone science and spectroscopy to progress beyond the proof-of-concept stage, a *killer app* is necessary, an application so lucrative that investment and social interest follow naturally [490]. Scientific use cases for iSPEX 2 are discussed in Section 6.6.2, focused on remote sensing of air and water. While low-cost in-situ electrochemical sensors are the norm for citizen science of aerosols [495, 496], iSPEX 2 has the advantage of being more directly comparable and complementary to professional measurements from satellites and AERONET. Combining both types of low-cost sensor delivers the best of both worlds. In principle, iSPEX 2 can be applied to any field where visible-light spectroradiometry or spectropolarimetry is used. Potential commercial use cases include characterisation of paint colour, electric lights, and food freshness, and detection of contamination and health issues like skin cancer [98, 346, 349, 490]. Future work is necessary to develop these use cases and, by demonstrating the quality and value of smartphone measurements, identify the killer app.

7.3 Spectropolarimetry of floating debris

Spectropolarimetry plays a prominent role in the future outlook for remote sensing of water. In an interesting parallel with smartphone science (Section 7.2), despite many scientifically interesting proof-of-concept studies, polarimetry has not yet been embraced by the wider community [165]. The upcoming PACE mission, with its SPEXone and HARP-2 instruments, will provide multiangular hyperspectral polarimetry with global coverage [86], offering many new opportunities for research [238]. Initially, these will be focused on aerosol and climate science and on reducing the uncertainty in atmospheric correction algorithms [185,188,421]. Specific areas of interest for water research include the detection and characterisation of coccolithophores [21], oil spills [497], suspended particles [163, 164], and wind and wave conditions [240]. Spectropolarimetry also provides new opportunities for reducing uncertainties from glint and atmospheric correction (Section 7.1). These use cases also apply to other satellite instruments, airborne sensors, and terrestrial sensors including iSPEX 2. Scientific use cases for spectropolarimetry are discussed further in Chapter 6 and in Sections 1.2.3 and 1.3.3.

This section contains the initial results from a study on spectropolarimetry of floating debris. This work was done as part of the OP^3 project[24] funded by ESA and led by Shungu Garaba, Tristan Harmel, and Paolo Corradi. Within OP^3, we are investigating the spectropolarimetric properties of light scattered by micro- and macroplastics and other floating debris through radiative transfer simulations [498] and laboratory experiments [476]. The aim of the project is to determine the value of visible-light spectropolarimetry in a marine debris observing system [75].

Measurements were conducted during an ESA campaign in the Deltares Atlantic Basin[25] from 24 January–4 February 2022. The basin is 75 m long, 8.7 m wide, and 1.3 m deep, with a maximum water depth of 1.0 m. Its bottom is made of grey concrete and partially covered in sand. During the campaign, the basin was filled with clear, unaltered tap water. It features a wave cradle capable of producing waves with a realistic spectrum, similar to natural waves in the North Sea. Various types of macroplastics and other debris, such as plywood and rope, were manually thrown into the basin and studied as they floated on the water surface.

Two instruments were used, namely the groundSPEX spectropolarimeter[26] and a FLIR BlackFly BFS-U3-51S5PC-C RGB polarisation camera. GroundSPEX performs snapshot hyperspectral measurements of radiance and polarisation within its 0.9°-diameter field of view through the SPEX technique [175], further described in Section 6.2. Its original calibration in 2011–2014 is described in [125] and laboratory tests indicated that these calibration data were still valid. A Python implementation[27] of the original data processing and demodulation pipeline was used. The BlackFly camera is based on a Sony IMX 250 MYR sensor with a double Bayer pattern (Section 1.2.2), consisting of a layer of RGB filters and a layer of polarisation filters (0°, 45°, 90°, and 135°). The calibration of a different camera based on the monochromatic version of this sensor is described in [499]. The BlackFly data were processed using the Polanalyser package[28]. The BlackFly camera was mounted on top of groundSPEX so that they were roughly aligned. Observations were done at a nadir angle of 40°, following the standard protocol for above-water radiometry [120, 209]. The basin was illuminated by dozens of fluorescent lights spread across the ceiling, which for safety reasons could only be turned off during one measurement session. For additional light, a halogen lamp was positioned next to the instruments and angled toward their field of view, with an effective azimuth angle of ~90° and zenith angle of ~35°.

Initial results from the groundSPEX measurements (Figure 7.1) showed a moderate degree of linear polarisation ($0.05 \leq P_L \leq 0.15$) for several types of plastic debris. In Figures 7.1b–7.1d, P_L appears to increase as the total radiance decreases at $\lambda > 700$ nm, which is similar to the Umov effect [500, 501]. The high values of P_L seen at $\lambda > 710$ nm in Fig-

[24] Ocean Plastics Polarization Properties, funded through the Discovery Element of the European Space Agency's Basic Activities contract no. 4000132037/20/NL/GLC, https://uol.de/en/icbm/marine-sensor-systems/current-projects/ocean-plastics-polarization-properties-op3

[25] https://www.deltares.nl/en/facilities/atlantic-basin-3/

[26] Courtesy of RIVM.

[27] https://github.com/burggraaff/SPEX

[28] https://github.com/elerac/polanalyser

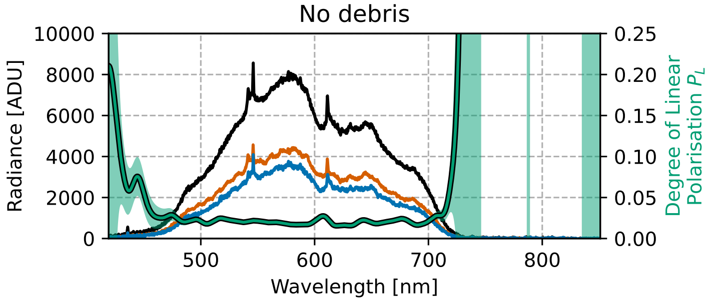
ure 7.1a are the result of measurement noise. P_L was otherwise approximately spectrally flat for virtually all types of debris investigated. Because groundSPEX is a spot radiometer without imaging capabilities, it is difficult to determine the mechanism causing the observed polarisation. The line features seen in Figures 7.1a and 7.1b were caused by the fluorescent ceiling lights and are present in most data sets. The offset between the two groundSPEX channels seen in each panel, most clearly in Figure 7.1a, is due to a difference in transmission between the two channels and is corrected in the demodulation algorithm, although future work is necessary to improve the accuracy of this correction.

Similar trends were found with the BlackFly camera. RGB polarimetric images of the protective foam sample taken roughly simultaneously with the groundSPEX observations (Figure 7.1d) showed a similar degree of polarisation, namely $0.0 \leq P_L \leq 0.2$ (Figure 7.2). Comparing the RGB photograph and G-band P_L image suggests two primary mechanisms for polarisation. First, as the foam floated near the water surface, small puddles formed on top of it, which can be identified in both images. Second, the foam was slightly crinkled, resulting in diagonal lines that can again be identified in both images. Thus, both the plastic itself and its interactions with the water surface appear to be sources of polarised light. Both mechanisms were also seen in images of plastics fully submerged just under the water surface or floating entirely on top of it. Based on calibration data, it will be possible to match the field of view of groundSPEX with specific pixels in the BlackFly images to further investigate the sources of polarisation.

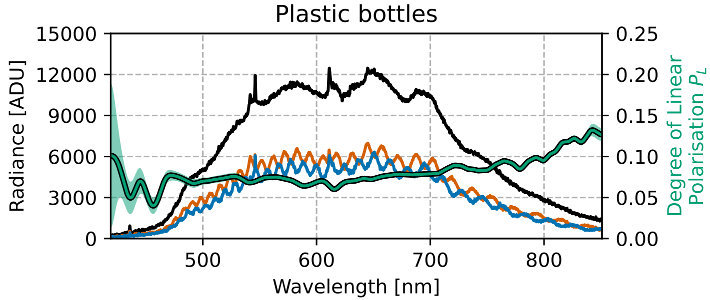
The preliminary conclusion from this measurement campaign is that many types of floating debris impart a measurable polarisation ($0.05 \leq P_L \leq 0.20$) on reflected light, making polarimetry a useful addition to a marine observing system. Both debris itself and its interactions with the water surface seem to induce polarisation. The observed P_L represents a situation where the sensor field of view is entirely filled with debris, which is not realistic for satellite sensors. Even in garbage patches, floating debris covers a small fraction of the 10 m–10 km satellite pixel footprints. It is unlikely that spectropolarimetric sensors on satellites will be able to distinguish the polarised reflectance of debris from other constituents, bubbles and whitecaps, specular reflections, and atmospheric signals. Simulations suggest that small microplastics are more suitable for satellite detection than macroplastics [498]. This limitation does not apply to air- and shipborne sensors, which have much smaller pixel footprints that can realistically be fully covered by a piece of debris. Thus, we suggest that polarimetry may be used to aid in the detection of floating debris from airborne platforms like UAVs and from ships, in particular to better distinguish between debris and water when the two are similarly bright, and to distinguish between types of debris. Since P_L appears to be largely spectrally flat, hyperspectral measurements are not necessary and an RGB camera can be used.

Future work on this experiment will include investigating all collected data in more detail, improving the data processing pipeline, and more precisely determining the uncertainties on the data and results. Future experiments should focus on adding other constituents such as phytoplankton, CDOM, suspended minerals, and microplastics to determine the contribution of debris to the overall reflectance in realistic settings.

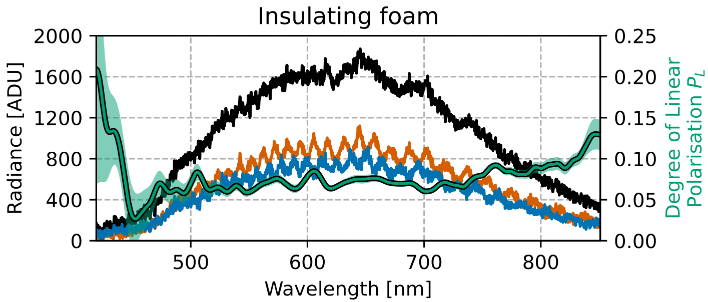
Lastly, we have developed a goniometer setup for measuring the bidirectional polarised reflectance distribution functions (BPDFs) of micro- and macroplastics in a laboratory setting (Figure 7.3). Using groundSPEX, samples are observed at four instrument elevation angles, corresponding to the viewing angles of SPEXone and the Mobley protocol [86, 209]. A laser-driven light source provides broad-spectrum light at arbitrary azimuth and elevation



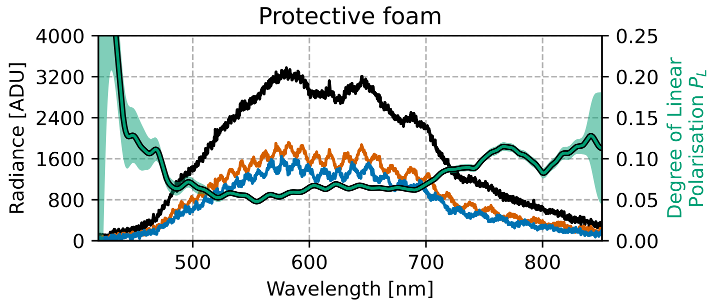
(a) Water without debris. 9 cm waves, with ceiling lights on.



(b) Plastic bottles. 9 cm waves, with ceiling lights on.



(c) Dark grey insulating foam. 9 cm waves, with ceiling lights off.



(d) Transparent protective foam. 9 cm waves, with ceiling lights off.

Figure 7.1: Upwelling radiance spectra of four targets observed with groundSPEX. The calibrated data from the $\pm Q$ channels are shown in blue and red, the total radiance in black, and P_L in green. The shaded green area shows the uncertainty in P_L, estimated by the demodulation fitting routine.

7

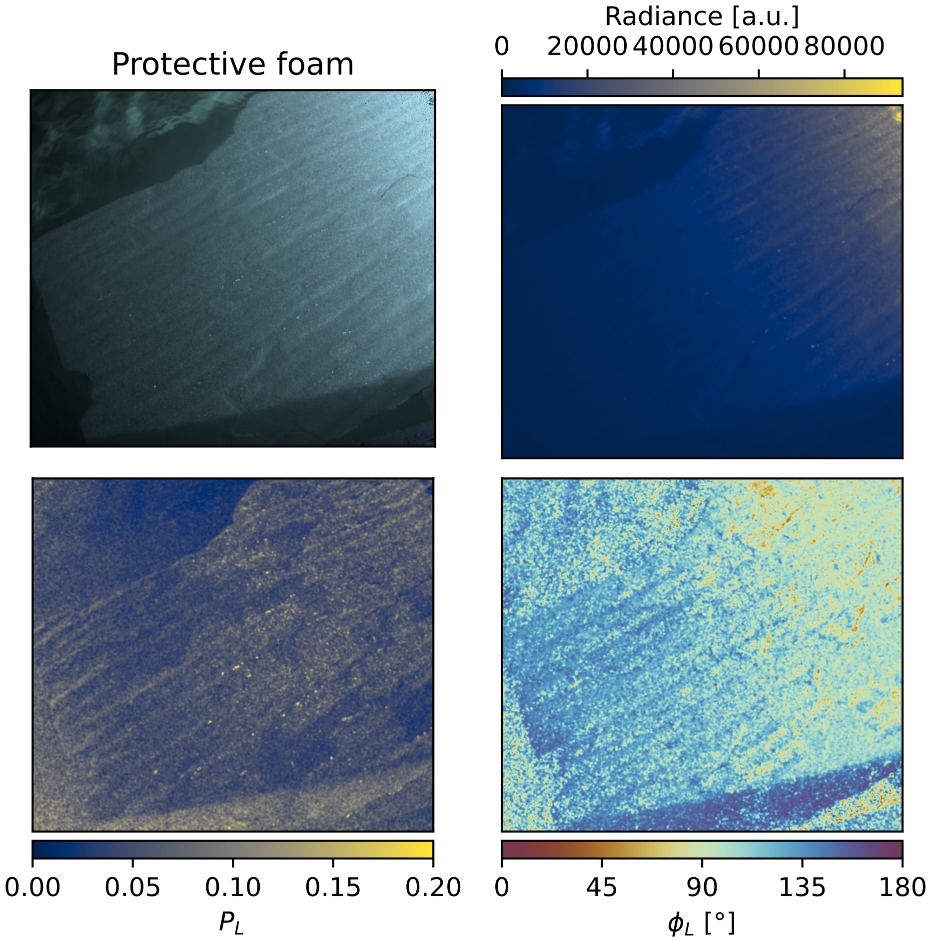


Figure 7.2: BlackFly observations of floating protective foam. The data were taken during the same session as Figure 7.1d, but not simultaneously. The RGB photograph (top left) is not white balanced and is slightly bluer than true colour. The G-band radiance (top right), P_L (bottom left), and ϕ_L (bottom right) images were convolved with a two-dimensional Gaussian with σ = 3 pixels to reduce noise. The zero-point on ϕ_L is arbitrary.

angles. In the future, polarised input light may be used to measure the full Mueller matrix (Section 1.2.3). The primary aims of this experiment are to validate BPDF simulations [498] and to provide the community with additional BPDF data for a wide variety of samples. Similar work has recently been done on characterising the effects of turbidity and salinity on the BPDF of water [502, 503] and on determining the BPDFs of various types of land cover and vegetation [166, 504, 505]. These data are valuable inputs for atmospheric correction algorithms, (exo)planetary atmosphere models, and vegetation reflectance models [166, 188, 506]. The goniometer setup has been built and is currently being commissioned.

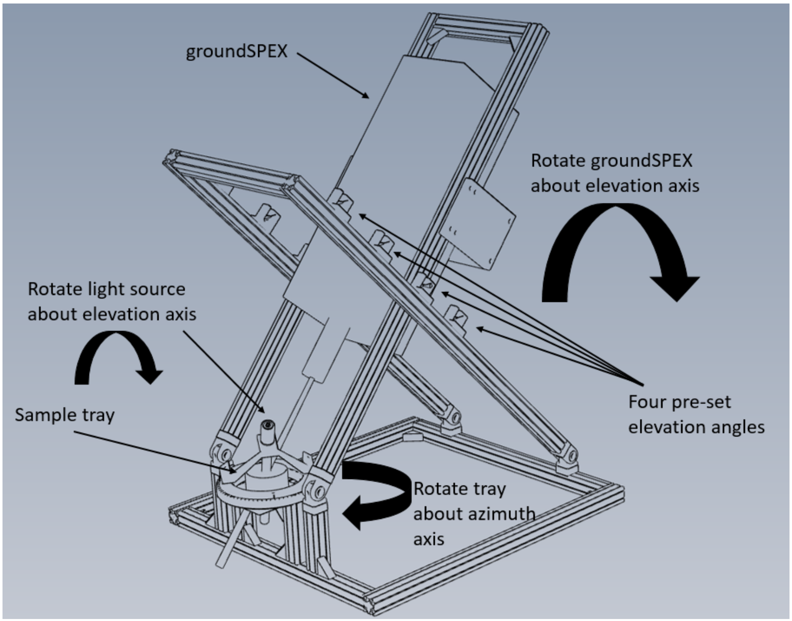


Figure 7.3: Render of the laboratory setup for measuring BPDFs with groundSPEX. The most important elements and degrees of freedom are indicated. Image courtesy of Remko Stuik.

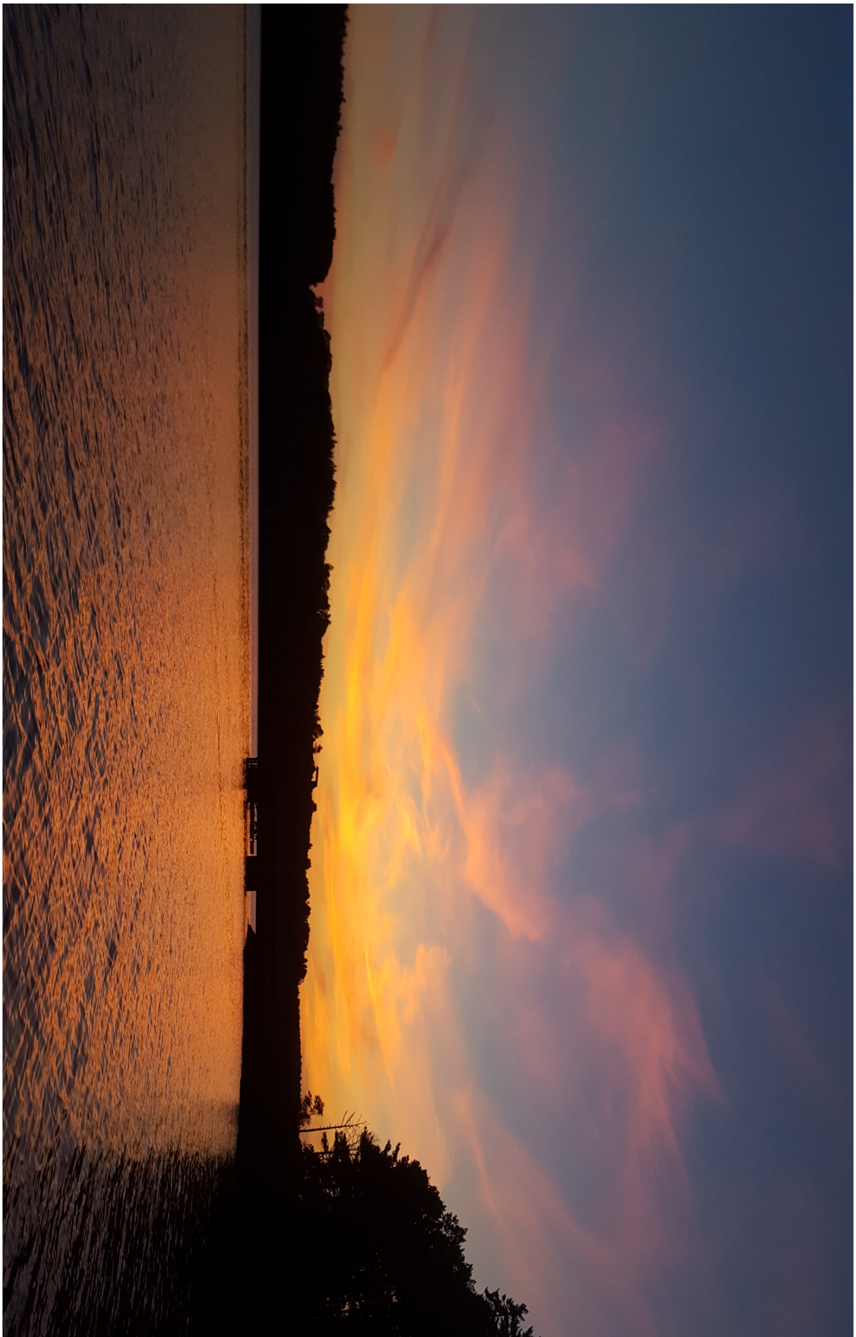


Figure 7.4: Sunset over the Damariscotta River. Photograph taken at the Darling Marine Center, Walpole, Maine, USA, on 9 June 2019.

7.4 Conclusions and recommendations

This section provides a summary of the primary conclusions and recommendations of this thesis. A full summary of the thesis, in Dutch and in English, is provided after the bibliography.

Conclusions

1. Colour blindness significantly increases the uncertainty on Forel-Ule colour measurements for a significant fraction of users (Chapter 2).
2. Consumer cameras, including smartphone cameras, can perform professional-grade spectroradiometry when using RAW data (Chapters 3 and 4).
3. Spectral convolution of hyperspectral reflectance is often performed incorrectly, causing significant systematic errors (Chapter 5).
4. The iSPEX 2 add-on enables accurate spectropolarimetry using smartphone cameras (Chapter 6).

Recommendations

1. Vague terms like *water quality* should be replaced with specific quantities like constituent concentrations and inherent optical properties (Chapter 1).
2. Results should always be reported with an uncertainty estimate (Chapters 2, 3, 4, 5, and 7).
3. To ensure reproducibility and facilitate novel research, data should be published in full, including raw data and calibration materials (Chapters 2, 4, and 5).
4. To improve accessibility and data quality, citizen science protocols should be co-created with a diverse group of participants, including people with disabilities (Chapters 2 and 7).
5. To ensure consistency and reproducibility, instruments should be calibrated and characterised using standardised methods, and calibration data should be published (Chapters 3 and 4).
6. To reduce measurement uncertainties, calibration materials should themselves be calibrated thoroughly and regularly (Chapter 4).
7. To achieve a realistic uncertainty estimate, multiple methods should be compared, such as replicate observations and analytical propagation (Chapters 4 and 7).
8. To reduce systematic errors, assumptions about the accuracy of approximations and mathematical methods should always be challenged or justified (Chapter 5).
9. To ensure future compatibility and optimal accessibility, smartphone science add-ons should be designed as universally as possible (Chapter 6).
10. To maximise adoption and impact, citizen science tools should be designed with both top-down and bottom-up research in mind (Chapters 6 and 7).