CVPR
Paper Reading Group

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What Is the Space of Attenuation Coefficients in Underwater Computer Vision?

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Abstract

Underwater image reconstruction methods require the knowledge of wideband attenuation coefficients per color channel. Current estimation methods for these coefficients require specialized hardware or multiple images, and none of them leverage the multitude of existing ocean optical measurements as priors. Here, we aim to constrain the set of physically-feasible wideband attenuation coefficients in the ocean by utilizing water attenuation measured worldwide by oceanographers. We calculate the space of valid wideband effective attenuation coefficients *in the 3D RGB domain and find that a bound manifold in 3-space sufficiently represents the variation from the clearest to murkiest waters. We validate our model using* in situ *experiments in two different optical water bodies, the Red Sea and the Mediterranean. Moreover, we show that contradictory to the common image formation model, the coefficients depend on the imaging range and object reflectance, and quantify the errors resulting from ignoring these dependencies.*

1. Introduction

The interaction between solar radiation and the upper ocean fuels physical, chemical, and biological processes; and as a result water attenuates light in a wavelength-dependent manner giving the ocean its color and other optical properties [13, 14]. Due to these wavelength-dependent processes, underwater images suffer from reduced contrast and color distortions. As the effect also depends on the distance of the objects, the image degradation is local and cannot be corrected by global operations. To correct the images, both the scene 3D structure and water properties need to be known. While 3D reconstruction is receiving considerable attention, there is almost no research on the range of water properties with respect to computer vision.

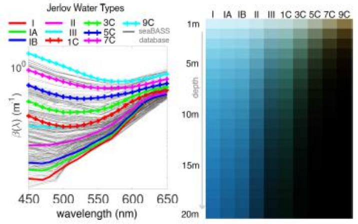


Figure 1. **Water types.** [Left] Based on the attenuation coefficient $\beta(\lambda)$ measurements from a global expedition between 1947-48 [25], 10 optical classes have come to be known as *Jerlov Water Types* [24]. Types I-III are oceanic waters that range from very clear to slightly murky, and those suffixed with 'C' represent coastal waters with increasing turbidity from 1 to 9. Gray lines represent 280 randomly chosen observations from a database [50] that contains more than 60,000 *in situ* measurements taken using modern day equipment between 1989-2015. [Right] RGB simulation of the appearance of a perfect white surface viewed in 1-20m depth in different water types. Note that the common notion that water attenuates red colors faster than blue/green only holds for oceanic water types. We use Jerlov water types to constrain the space of attenuation coefficients in the RGB domain.

brown, black, or even red [6]. Transmittance describes visibility which we might label as ranging from 'crystal clear' to 'murky', and it is a function of the wavelength-dependent attenuation coefficient of the water body and the distance light has to travel. The attenuation coefficient for the global ocean shows significant spatial and temporal variation as it depends on the concentration of organic and inorganic substances in the water column. How and when their concentrations change depends on complex interac-

E. Trucco & A. Olmos

$$K \sim [e^{-GR_c} - e^{-cR_c}]$$

TABLE I
TYPICAL PARAMETER VALUES IN THE INVERSE FILTERING PROCESS

Variable	*Ranges*
K (weight constant)	0.9 - 0.2
c (attenuation coefficient)	water type (m^{-1}) 0.323 bay 0.252 coastal 0.049 deep ocean
R_c (depth)	order of meters
Fl (focal length)	.035 m (typical value)

E. Trucco and A. Olmos, “Self-tuning underwater image restoration,” IEEE Journal of Oceanic Engineering, vol. 31, no. 2, pp. 511–519, 2006.

Introduction

Water attenuates light in a wavelength dependent manner

↓

Underwater images suffer from reduced contrast and color distortions

Related Work

Single image reconstruction

assume wavelength independent attenuation

used fixed coefficients for reconstruction,

Related Work

Other methods

↓

multiple images
recovered channel dependent optical depth
related parameters

Related Work

Basic estimation method for attenuation coefficients

↓

acquire an image of a known calibration target at known distances

↓

however this requires external hardware and distance measurement

The author's main work

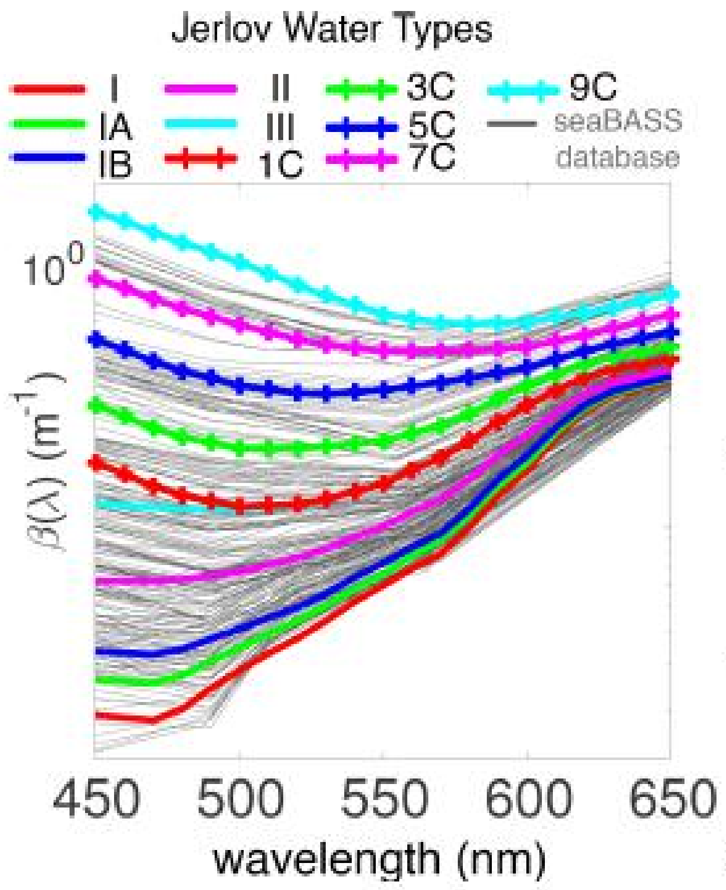
Using the optical classification of natural water bodies they derive the loci of all physically meaningful RGB attenuation coefficients for underwater imaging.

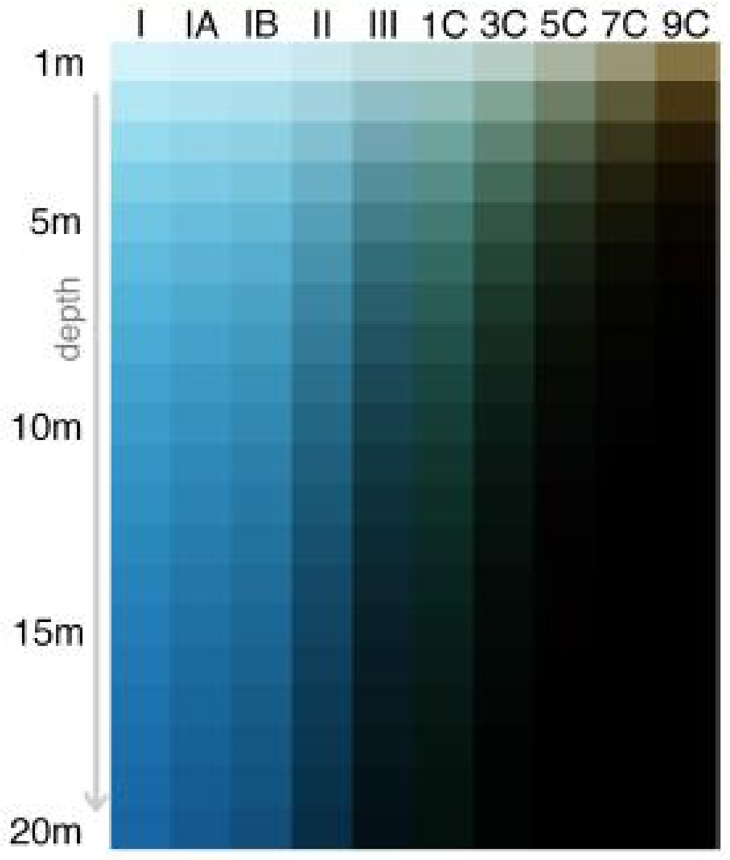
Sensitivity of reconstruction to error in attenuation coefficients

They validate their proposed loci by in situ experiments through scuba diving in two different water bodies: the Red Sea (tropical) and the Mediterranean (temperate).

The authors use the water bodies measured by oceanographers throughout the world to limit physically feasible broadband attenuation coefficients in the ocean and calculate the effective attenuation coefficients of the effective broadband in the RGB domain

Water types--Jerlov Water Types[1][2]





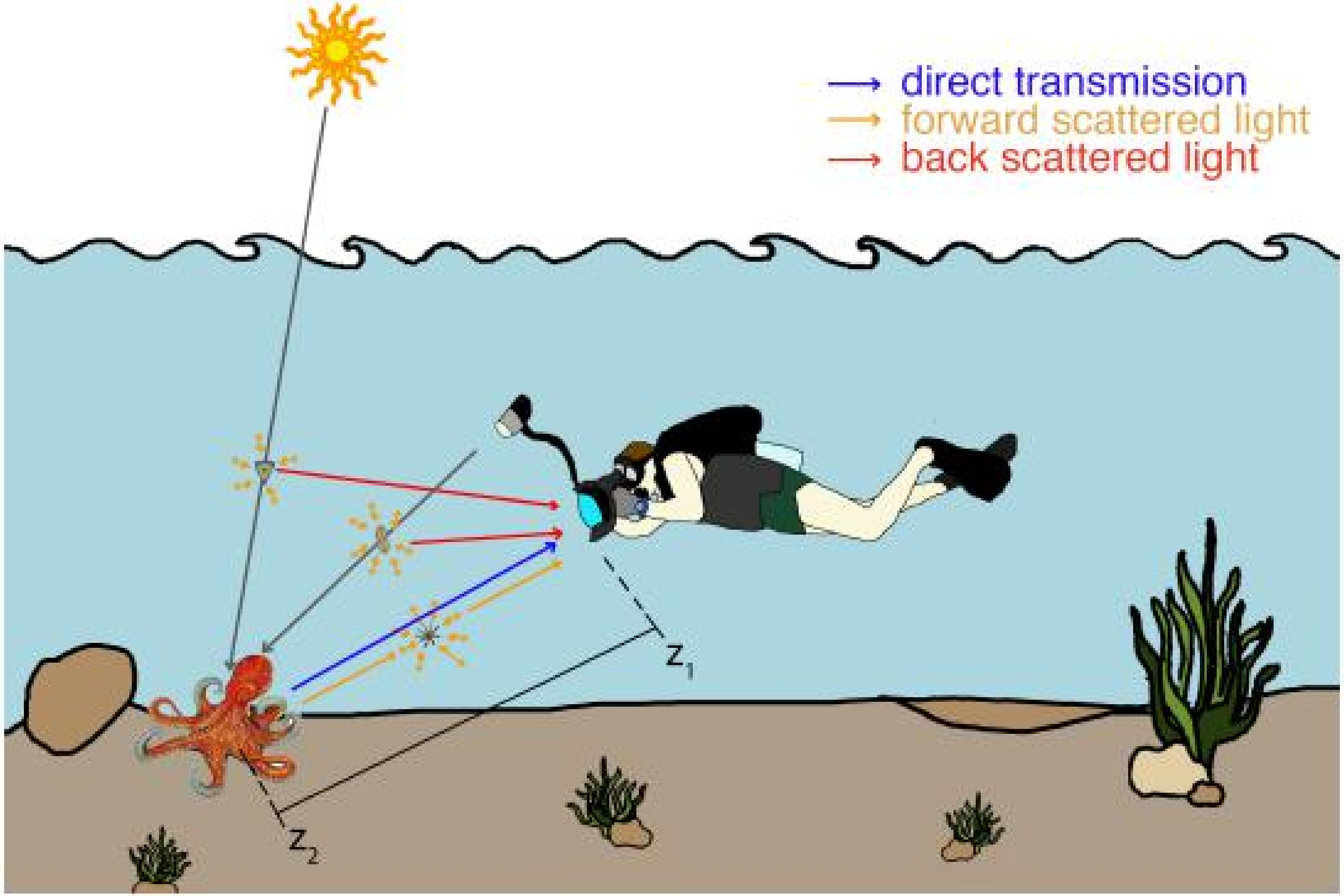
[1] N. Jerlov. Irradiance Optical Classification. Elsevier, 1968.

[2] N. Jerlov and A. (Schooner). Optical Studies of Ocean Waters.Reports of the Swedish Deep-Sea Expedition, 1947-1948 ; v. 3: Physics and chemistry. Elanders boktr, 1957.

Absorption and scattering, determine the amount of attenuation light will experience as it travels and encounters these particles

↓

The total attenuation coefficient $\beta(\lambda)$ is their summed effect


direct transmission
forward scattered light
back scattered light
z_1
z_2

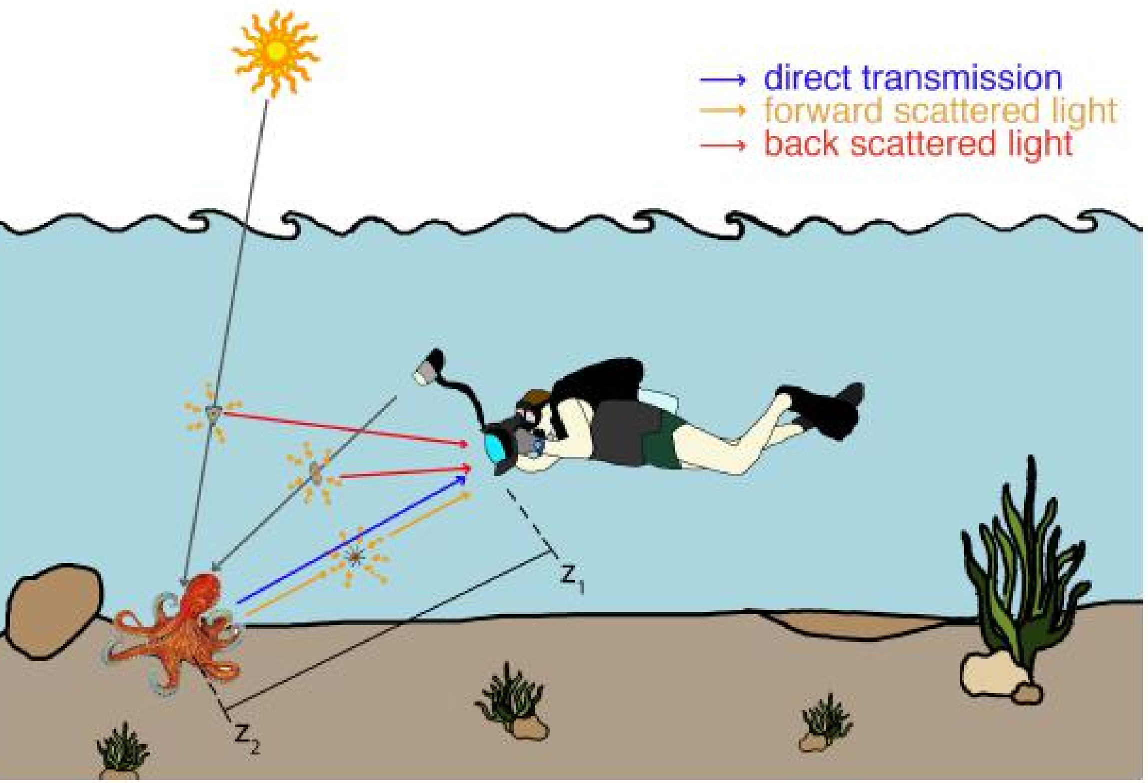


Image formation mode:

$$I_c(x) = D_c(x) + B_c(x)$$

D : directly transmitted light , attenuated by the water along the line of sight to the camera

B : the backscattering component (veiling light), carries no information about the scene

F : forward scattered light, it loses intensity and structure due to scattering along its trajectory before reaching the sensor

- Forward scattered light is negligible
- only consider the direct transmission signal

By the Beer-Lambert law[1] :

$$D(z_2,\lambda) = D(z_1,\lambda)e^{-\int_{z_1}^{z_2}\beta(z',\lambda)dz'}$$

z_1, z_2 : the start and end points along the LOS,
λ : wavelength,
β : the attenuation coefficient of the water body

Assuming the water volume is spatially homogeneous

$$\beta(z,\lambda) = \beta(\lambda)$$

[1]Y. Y. Schechner and N. Karpel. Recovery of underwater visibility and structure by polarization analysis. IEEE J. Oceanic Engineering, 30(3):570–587, 2005.

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$$\beta(z,\lambda) = \beta(\lambda)$$

$$\boxed{D(z_2,\lambda) = D(z_1,\lambda)e^{-\beta(\lambda)\Delta z}}$$

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the apparent color of a surface captured by a sensor with spectral response $S_c(\lambda)$ at a distance z is:

$$\boxed{D_{\mathrm{c}} = \frac{1}{k}\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)\Delta z}}$$

$\rho(\lambda)$: the reflectance spectrum of the surface of interest,

$E(\lambda)$: the illumination irradiance,

k : a scaling constant governing image parameters

recover the unattenuated colors of the original scene, denoted by J_c:

$$J_c = D_c(z = 0)$$

When working with wideband cameras, it is common to express attenuation by wideband channels, simplifying

$$D(z+\Delta z) = D(z)e^{-\beta_c \Delta z}$$

β_c : the effective wideband attenuation coefficient

Two advantage:

1. it reduces the number of unknowns that need to be estimated for β to three, one for each color channel of an RGB camera.

2. by removing the wavelength dependency, it makes it possible for the term $e^{-\beta_c \Delta z}$ to be taken outside of the integration.

When the direct signal and range z are known or estimated,

$$\widehat{J}_c = D_c e^{-\beta_c z}$$

$$D(z+\Delta z) = D(z) e^{-\beta_c \Delta z} \Longrightarrow \beta_c = \ln\left[\frac{D_c(z)}{D_c(z+\Delta z)}\right] / \Delta z$$

$$\boxed{\beta_c = \ln\left[\frac{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)z}d\lambda}{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)(z+\Delta z)}d\lambda}\right] / \Delta z}$$

It can be seen that β_c depends on S_c, z, Δz, ρ and E, as opposed to $\beta(\lambda)$ that is a property of the water.

- Derive the loci of all physically meaningful RGB attenuation coefficients for underwater imaging.

Projected the attenuation coefficients $\beta(\lambda)$ of the 10 Jerlov water types into the RGB domain using the assumptions above.

$$\beta_c = \ln\left[\frac{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)z}d\lambda}{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)(z+\Delta z)}d\lambda}\right] / \Delta z$$

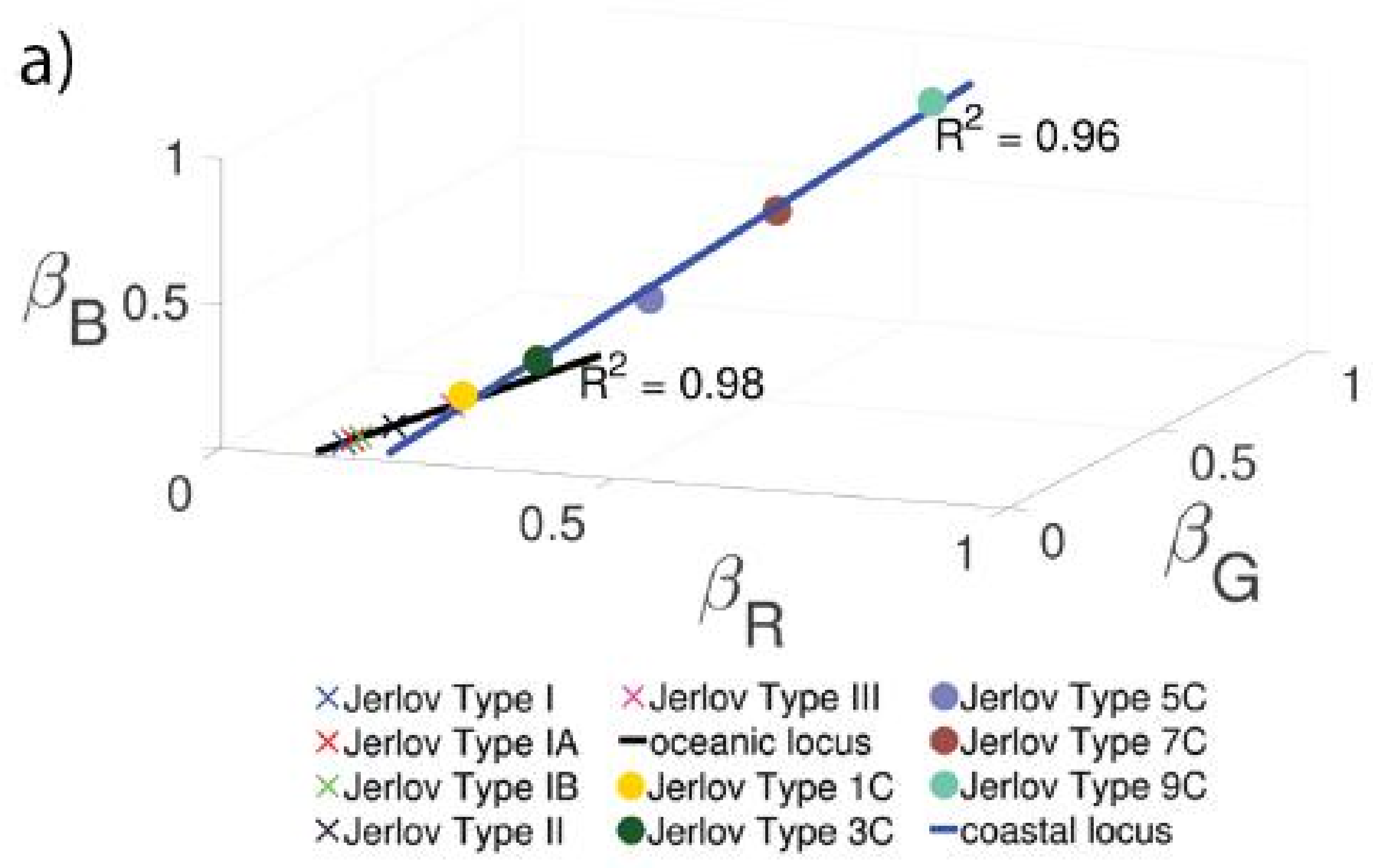


Figure a. shows the β_c values calculated for oceanic (denoted by X's) and coastal water types (filled circles), which fall on two lines in 3-dimensional space, where the color of each marker describes one of the water types from Fig. 1.

They used the spectral response curves of a Nikon D90 camera from the database of [1]. For simplicity, They assumed

$$\rho = E = 1; z_1 = 0, z_2 = 10m$$

[1] J. Jiang, D. Liu, J. Gu, and S. Susstrunk. What is the space of spectral sensitivity functions for digital color cameras? In IEEE Workshop Applications of Computer Vision (WACV), pages 168–179, 2013.

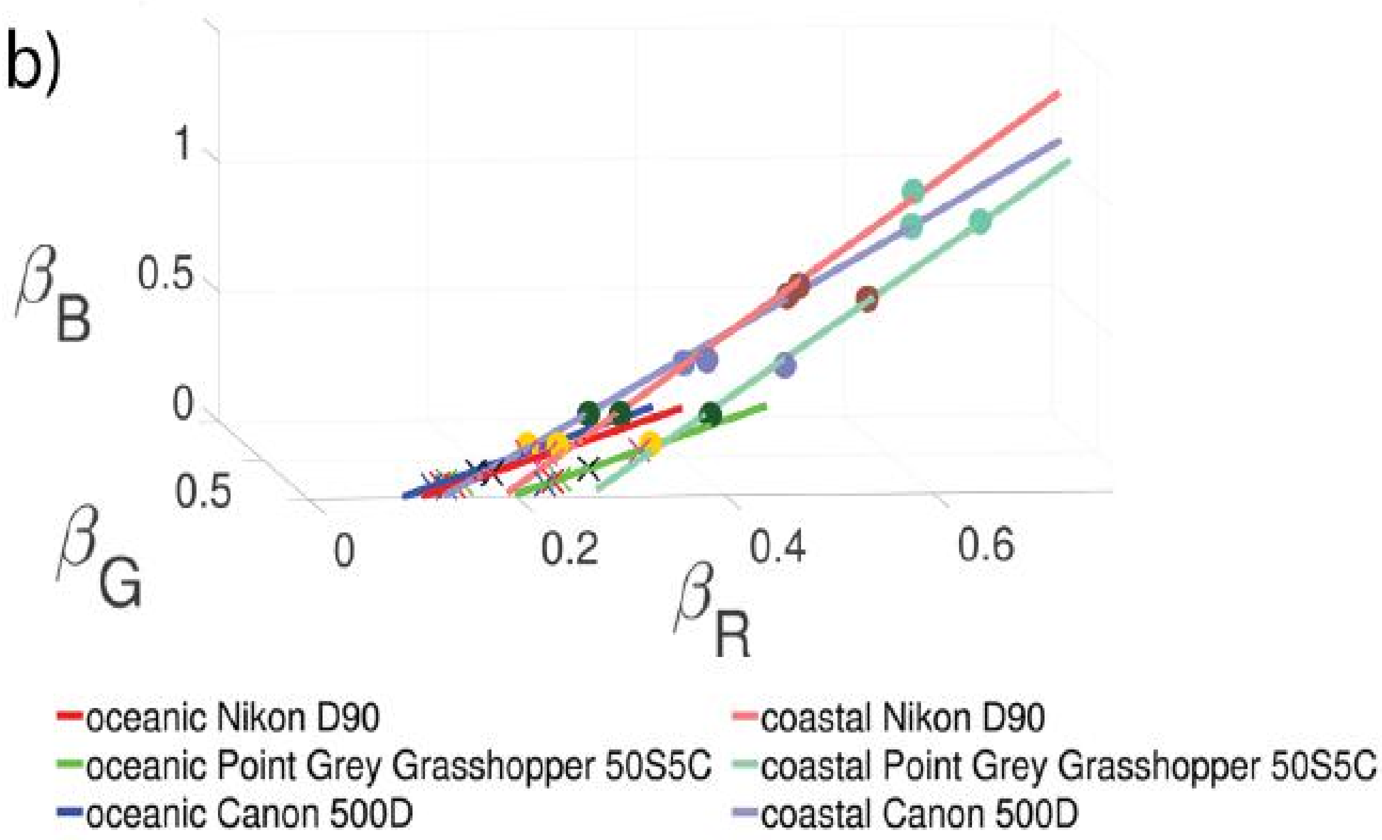
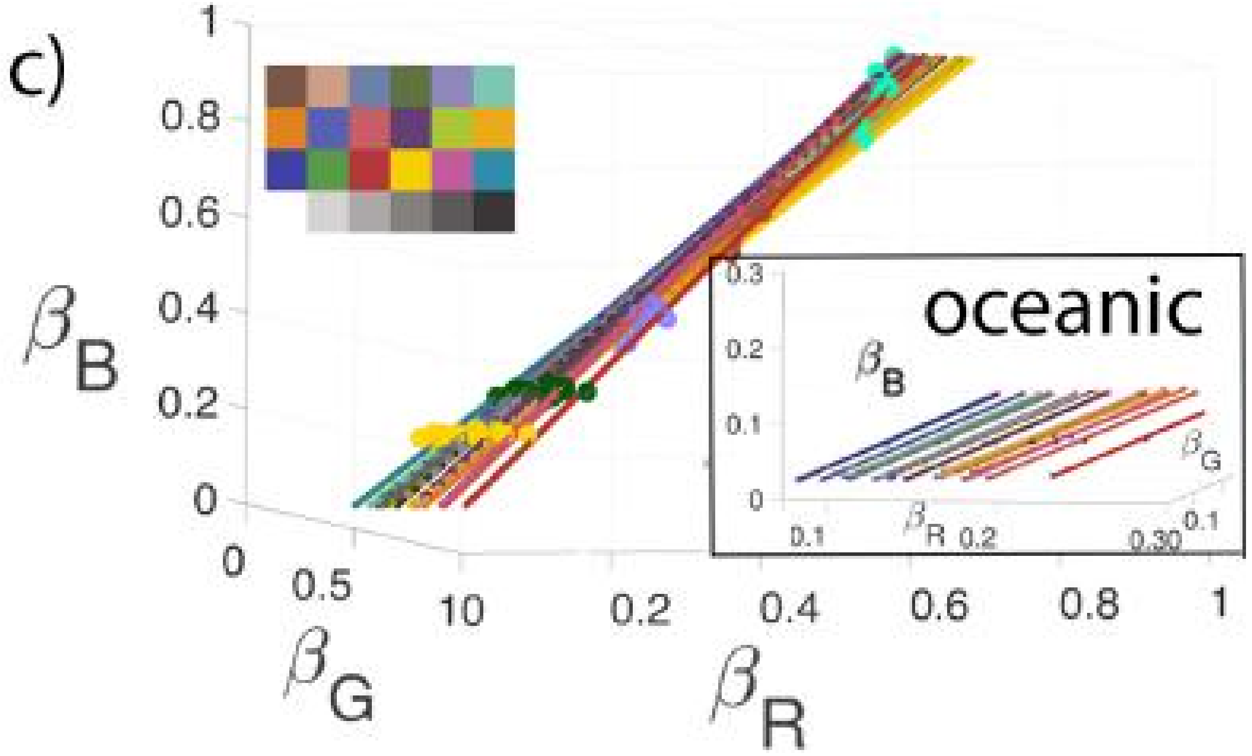
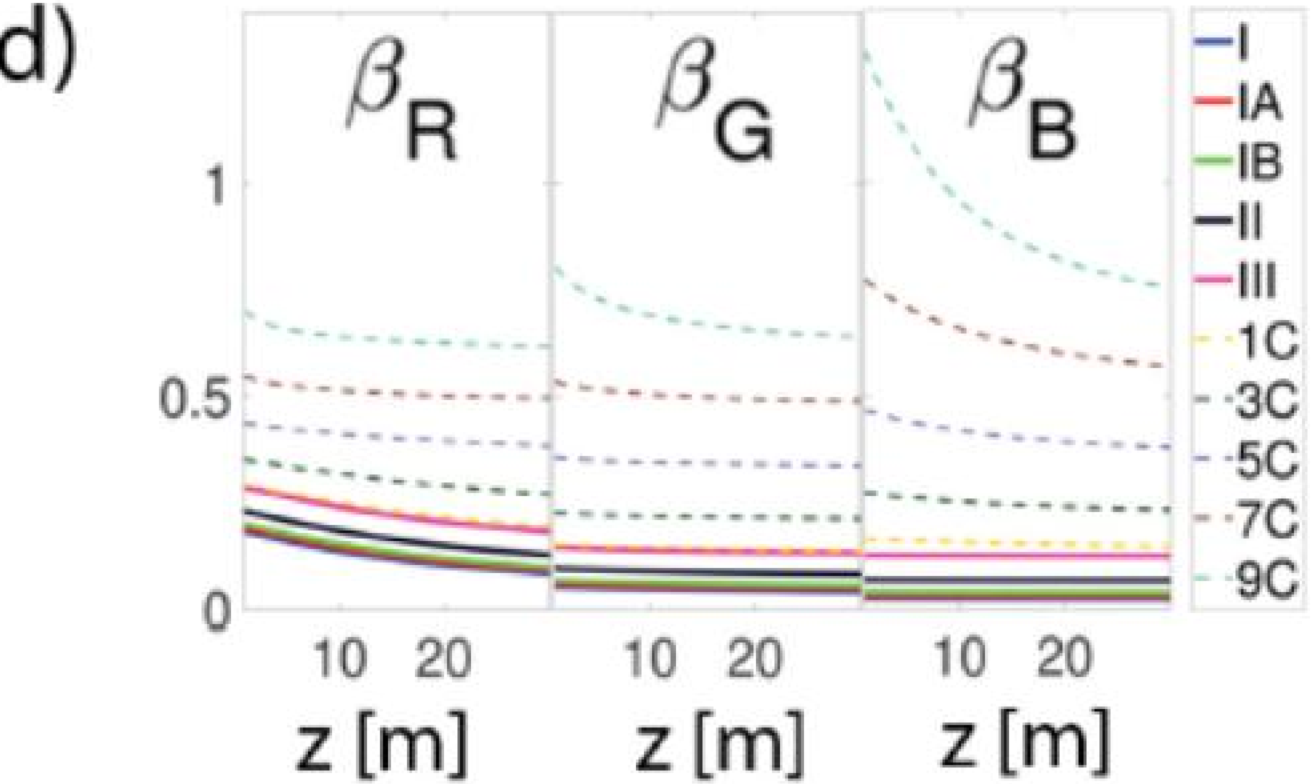


Fig. b shows how coefficients shift due to the response of three different sensors: Nikon D90, Canon 500D and Point Grey Grasshopper, whose spectral sensitivities they adopted from [1].

[1] J. Jiang, D. Liu, J. Gu, and S. Susstrunk. What is the space of spectral sensitivity functions for digital color cameras? In IEEE Workshop Applications of Computer Vision (WACV), pages 168–179, 2013.

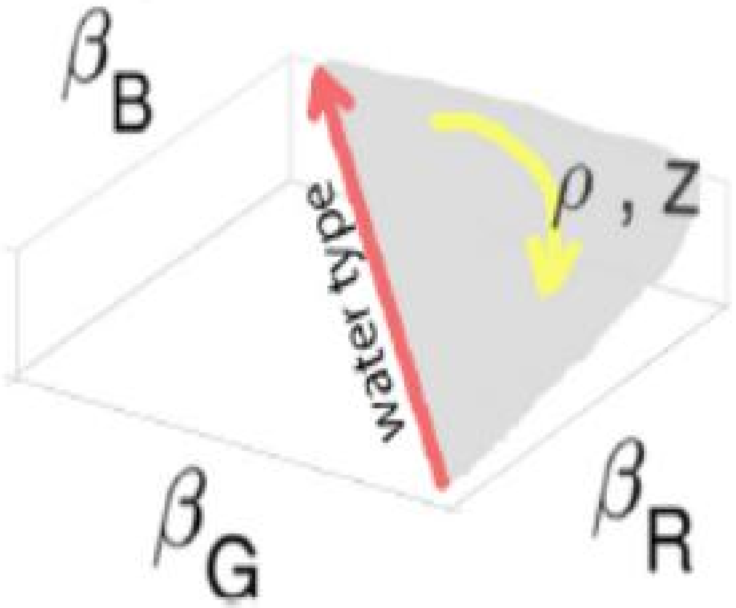


In Fig. c, they use radiance to demonstrate the combined effect on the patches of a Macbeth ColorChecker (XRite, Inc.) illuminated under the CIE 65 light.



In Fig. d, they used $z_1 = 1$ and varied z_2 up to 30 meters to calculate the shift of β_c. The z dependency is more prominent in water types where the attenuation coefficient changes rapidly within the sensitivity range of one of the color channels.

e)



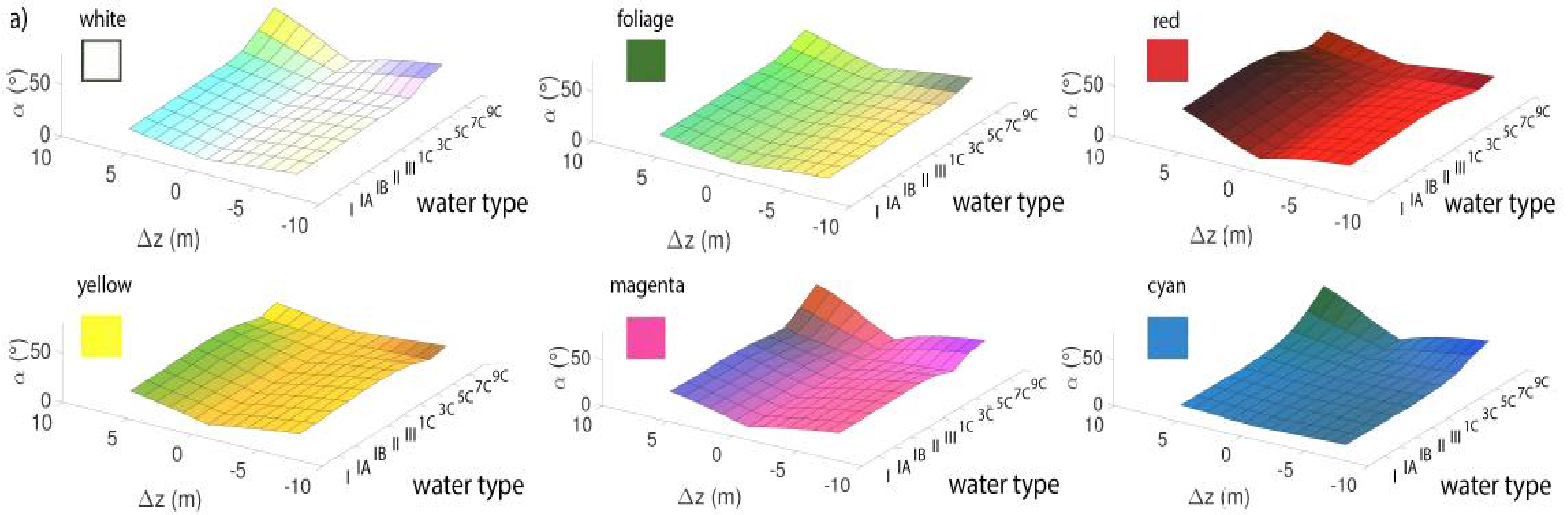
In Fig. e, for a given sensor, the locus of β_c (shown here for oceanic water) spans the area highlighted in gray, as the range and radiance are varied.

- Sensitivity of reconstruction to error in attenuation coefficients

In this section they examine how much these errors influence color reconstruction.

To examine the best-case scenario, they assume backscatter was removed properly, and look only at the error in compensating for attenuation of the direct signal.

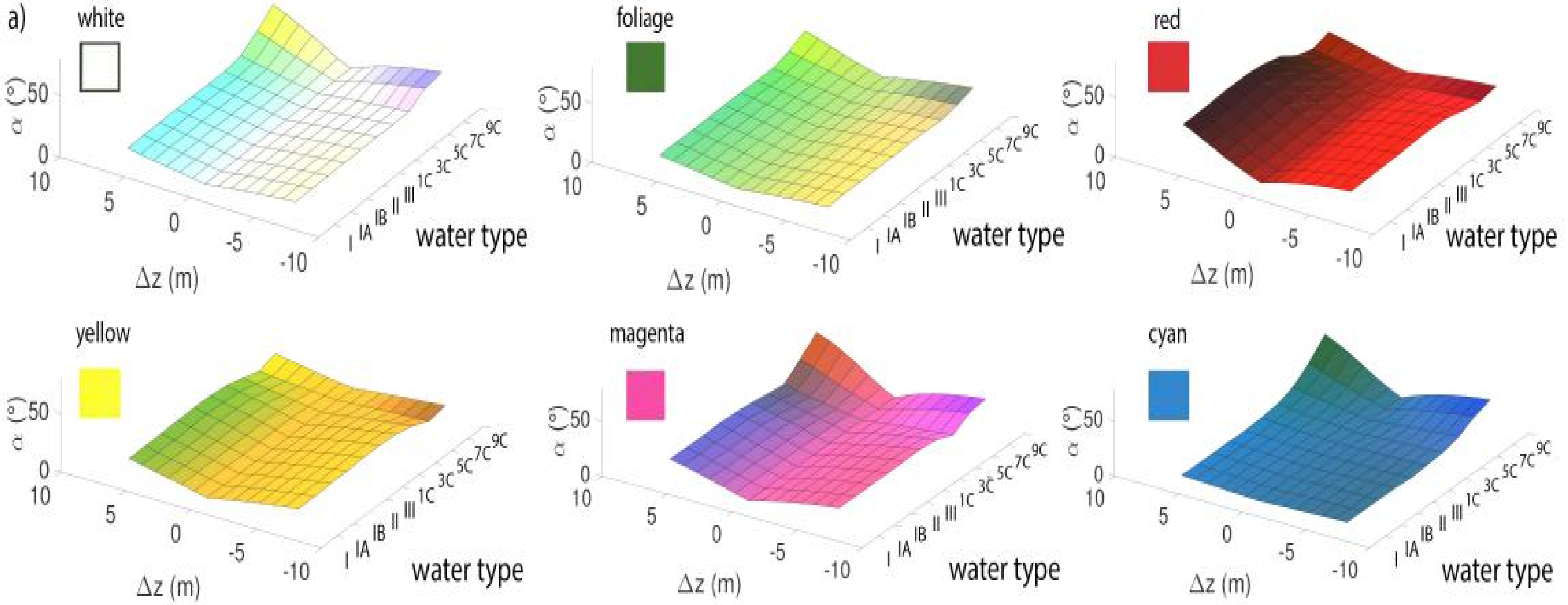
$$\boxed{\widehat{J}_c = D_c e^{-\beta_c z}}$$



Used the white, foliage, red, yellow, magenta and cyan patches of a Macbeth ColorChecker to demonstrate the errors in color correction when β_c is calculated using an incorrect range z

They quantify the error between the unattenuated color J and the one reconstructed $\hat{J}$ using $J_c = D_c(z=0)$ with incorrect β_c.

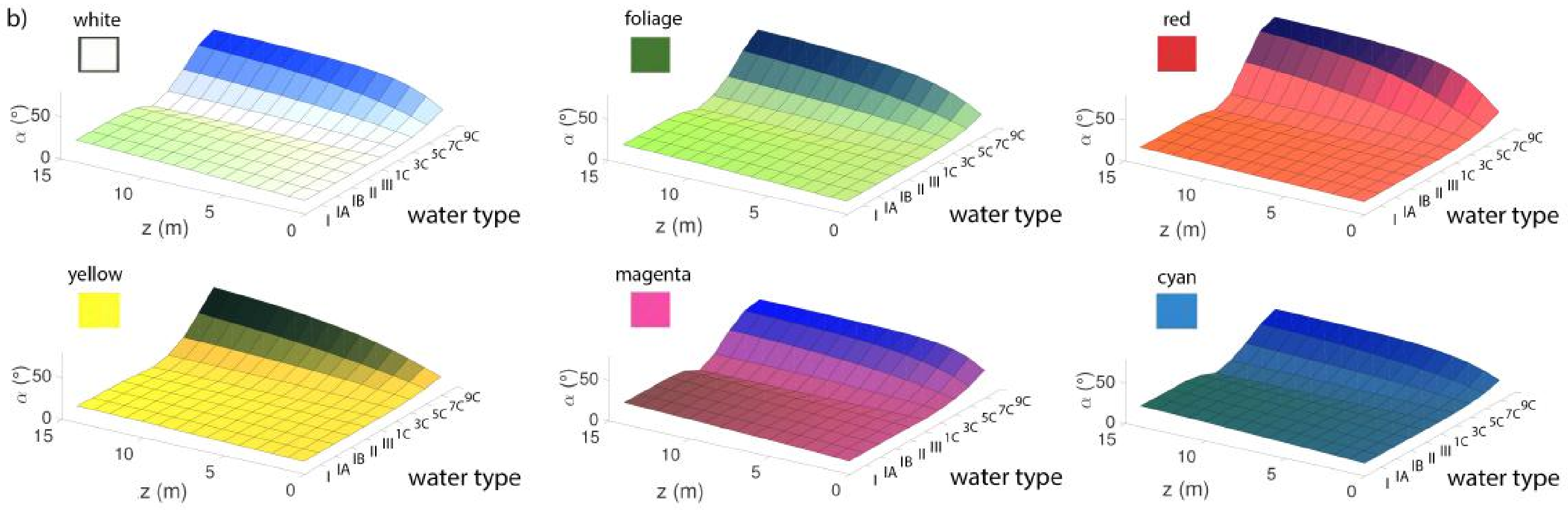
$$\cos\alpha = J \bullet \hat{J} \Big/ \left(|J|\,|\hat{J}|\right)$$



The z-axis shows the error ($\cos\alpha = \frac{J \bullet \hat{J}}{(|J||\hat{J}|)}$) between the unattenuated colors and those obtained by using incorrect β_c.

For oceanic waters, colors that contain red are most affected by larger errors in z.

In general, the hue of the reconstructed colors shifts whether β_c was estimated using longer or shorter ranges, and the larger the Δz, the more prominent this effect gets.



They simulated the same Macbeth chart patches in water type 1C, and visualize the errors resulting from estimated from other water types β_c

In both a) and b), errors are higher for coastal water classes, and for increasing ranges.

For visualization purposes, in both a) and b), they normalized the resulting colors for each patch by the maximum value encountered for that patch across all depths and water types.

In general, the error e_J in the recovered image J due to the error e_β in estimating β can be quantified as

$$\boxed{e_J = \frac{\delta J}{\delta \beta} e_\beta}$$

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take the derivative:

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take the derivative:

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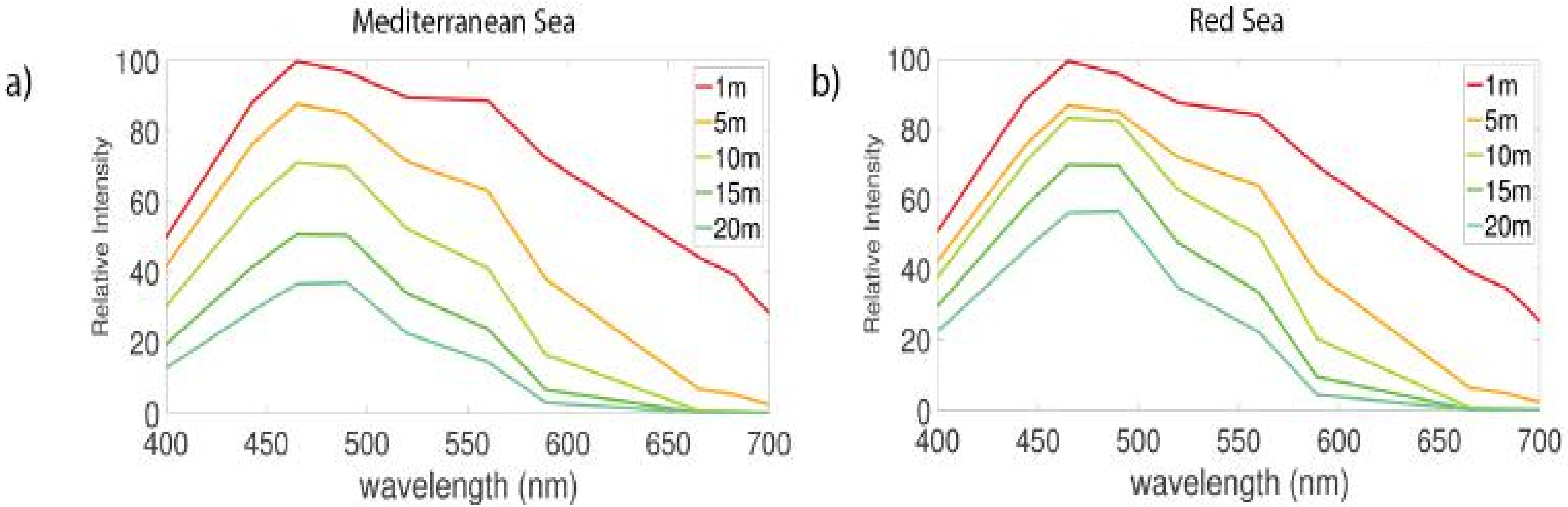
$$\boxed{\frac{e_J}{J} = z e_\beta}$$

Thus, the relative reconstruction error linearly increases with the object distance and the error in β_c.

- Experiments validating the model

The data was analyzed using the PROFILER software from the manufacturer. They then calculated the attenuation coefficient β according to Eq.

$$D(z_2,\lambda) = D(z_1,\lambda) e^{-\int_{z1}^{z2} \beta(z',\lambda)dz'}$$



They used $\beta_c = \ln\left[\frac{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)z}d\lambda}{\int S_c(\lambda)\rho(\lambda)E(\lambda)e^{-\beta(\lambda)(z+\Delta z)}d\lambda}\right] / \Delta z$ to calculate β_c using the measured attenuation, in different ranges.

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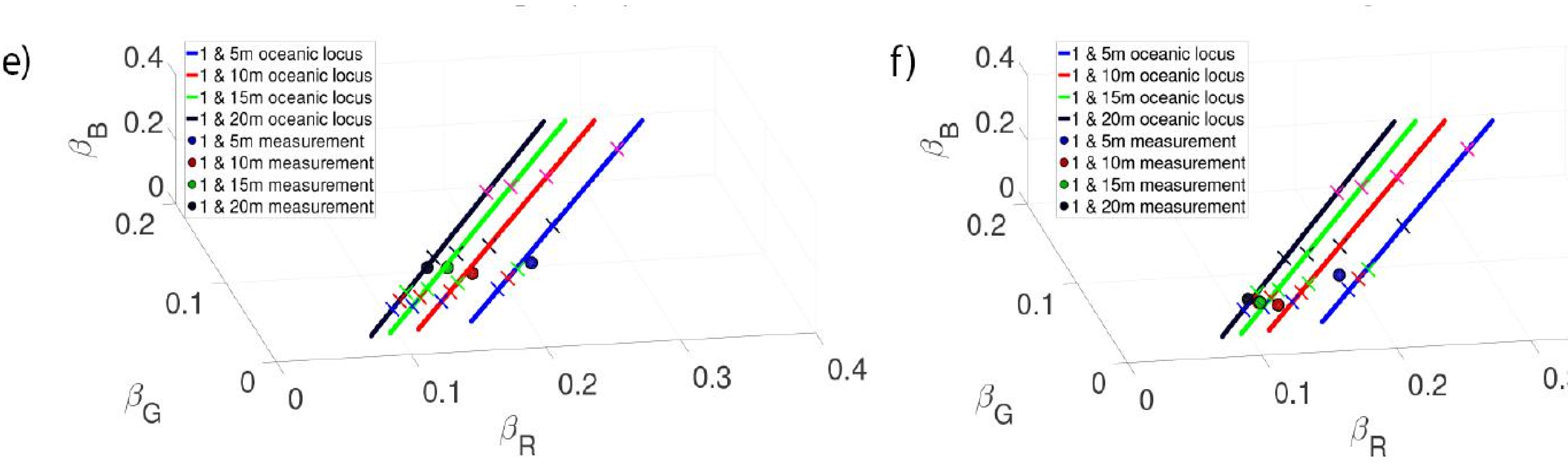
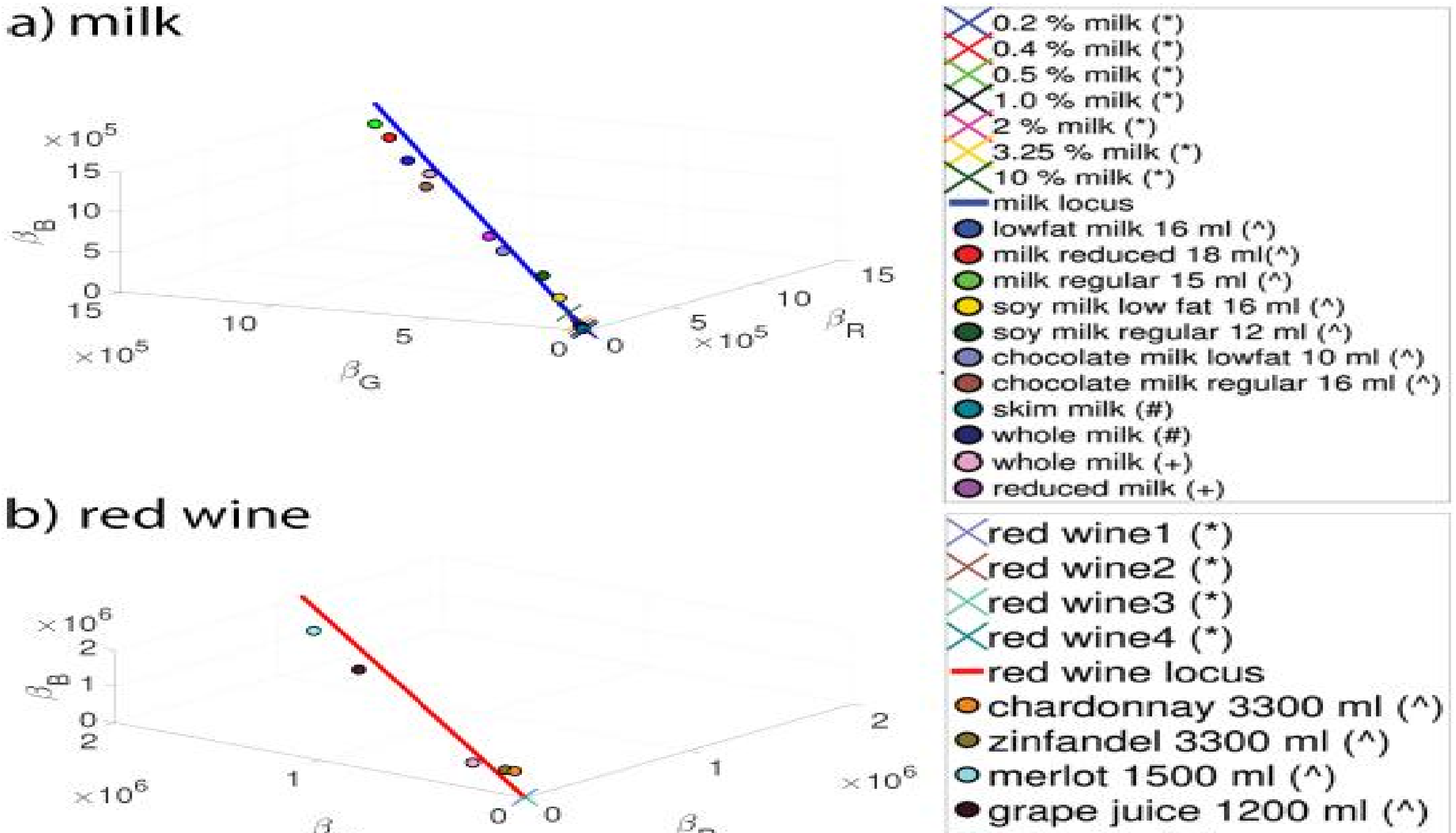


Application to Other Scattering Media

- they extend their methodology to milk and red wine, two commonly used participating media in computer vision and graphics. The optically important components in milk that affect its appearance are fat and protein molecules



Future work

- Use a pre-measured range map and reconstruct the image using distance-dependent coefficients.
- Using their analysis can infer the water type out of the coefficients, and consequently bio-optical properties, if the camera's sensitivity is known. Relating the ocean's biooptical
- Properties to the RGB domain will enable the useof RGB cameras in two new functions:

    1. for reliable ecological monitoring (e.g., plankton biomass estimation, harmful algal blooms, floods, oil spills, etc.);
    2. for validation of remotely sensed datasets of ocean color.

Q&A

Thank You!