
Information Content of Ocean Colour Data

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- What is Information Content?
- Instrument and Target Aspects
- Analysis of Information Content
- Retrievability of Parameters
- Multivariate Analysis - Principal Components and Intrinsic Dimensionality

Information Content of Ocean Colour Data

What is Information Content?

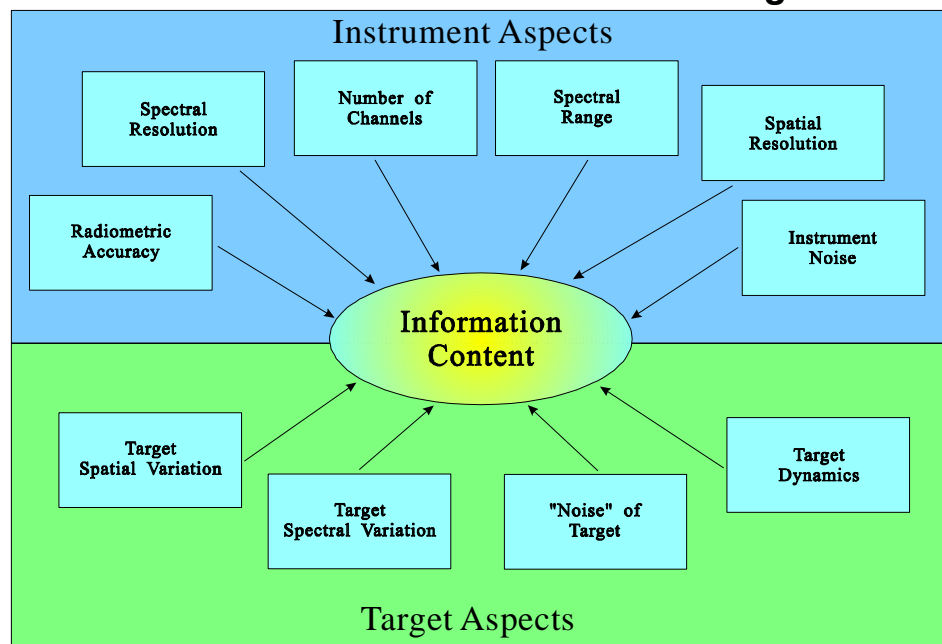
- ... the attempt to measure (i.e. quantify, enumerate) the “valuable information” in a set or stream of data
- different approaches worked out in information theory, statistics and applied sciences, depending on the problem to be solved (optimal coding strategies, data compression, parameter retrieval, ...)
- in the context of ocean colour remote sensing: requirements to spectral characteristics (resolution, number of channels, SNR) from the interpretation/applicational perspective

Parameters to Quantify or Handle Information Content:

- entropy (statistics, data coding)
- correlation (spectral, spatial)
- dominant factors (Factor Analysis)
- significant Ortho-Components (Principal Component Analysis, Karhunen-Loewe Transformation)
- *in our context leading to*
 - ⇒ **intrinsic dimensionality analysis**
 - ⇒ **“retrievability” of parameters**
 - ⇒ **error analysis of retrieval algorithms**

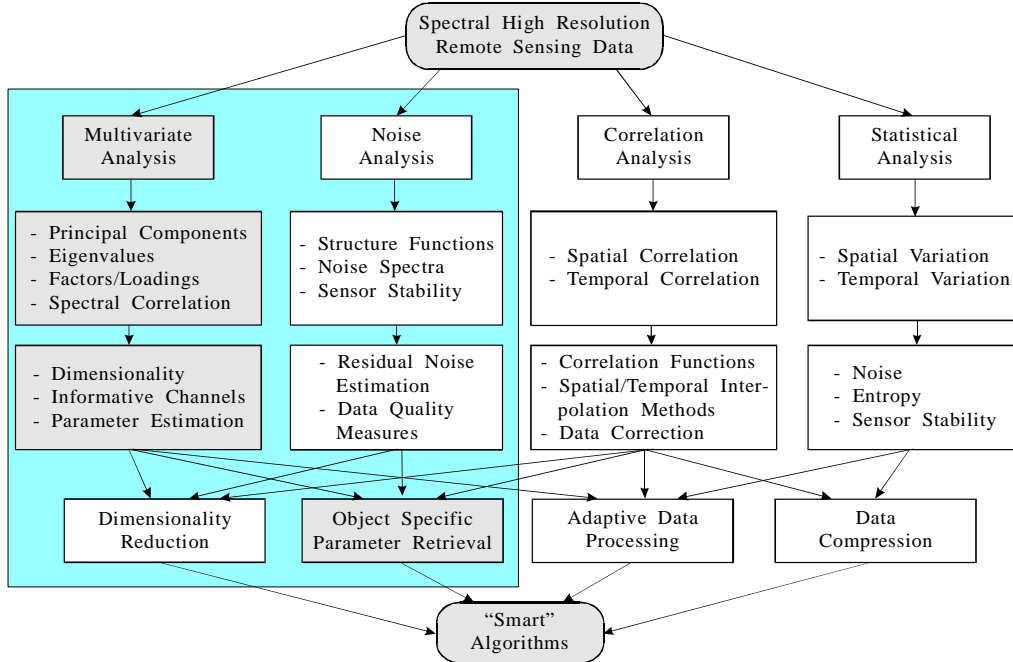
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Information Content of Remote Sensing Data



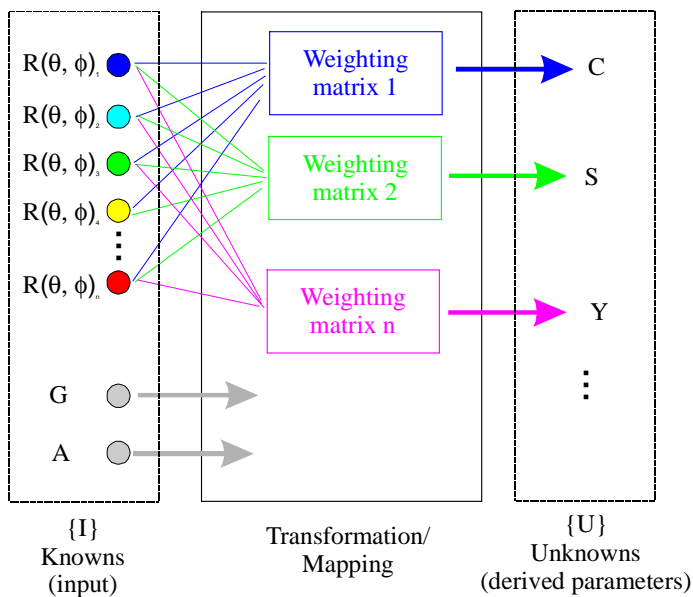
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Analysis of Information Content



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The Remote Sensing Problem



! The inverse task is analytically not solvable

? Which and how many parameters can be retrieved

? Which and how many channels contribute how much to each parameter

? How to construct an „optimal“ algorithm

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How to Perform an Information Analysis?

- Using experimental data, i.e. satellite and in-situ measurements:
 - quality/accuracy of the data often not known
 - influencing physical parameters not under control
 - problem: large number ($>10^4$) of data sets for various combinations of parameters necessary
- Using bio-optical and radiative transfer models:
 - clear understanding of mathematical and physical interdependencies
 - variability and number of parameters under control
 - problem: adequateness of the model for practical application

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Retrievability of Parameters - Basics

- We have measurements/simulations of spectral signatures, i.e. values of radiance/reflectance at certain λ (channels) with certain $\Delta\lambda$ (spectral halfwidth) and a given SNR and corresponding (bio-) physical parameters to be retrieved from the data $\{L_1, \dots, L_N, C, S, Y, \tau_A, \dots\}$
- generally no link between ONE parameter and ONE channel
- usually significant spectral correlation, at least in spectral subranges
- influence of the parameters spectrally overlapping
- statistical behaviour and interdependencies of parameters not predictable a priori
 - ⇒ first (and simple) test: numerical analysis
 - ⇒ second investigation: multivariate analysis

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Spectral Overlap of Different Constituents

Spectral range	Chlorophyll	Gelbstoff	Sediment
blue	absorption	strong absorption	scattering
green	scattering	weak absorption	scattering
red	scattering, absorption fluorescence	absorption	scattering

Atmosphere/aerosol: scattering at all wavelengths

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Retrievability of Parameters - Numerical Analysis

- Generate a large number of M spectra $\{L_1, \dots, L_N\} = f(C, S, Y, \tau_A)$ using radiative transfer model, N - number of available spectral channels
- degrade the "ideal" values by a given NE Δ L or relative "measurement" error
- analyse, how many spectra can be distinguished, i.e. are at least in one channel different to each other
- example for MOS channels: data set of 140.000 spectra for independently varying parameters of $C = 0..100 \mu\text{g/l}$, $a_Y(440\text{nm}) = 0..1$, $b_S(550\text{nm})=0..10$, $\tau_A = 0..0.25$

Relative Error [%]	0	1	3	5	7	10
Discriminated Spectra [%]	97	69	25	12	8	4

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Numerical Analysis - Conclusion

- for theoretical case of zero error the result is not too bad, disillusioning for realistic error values
- underlines high requirements to measurement accuracy
- more detailed analysis of error propagation and influence of single parameters possible, however, this seems not the adequate tool to handle correlations and interdependencies

⇒ ill-defined, multivariate problem which needs more sophisticated tools for analysis

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Retrievability of Parameters - Multivariate Analysis

- Multivariate analysis (e.g. factor analysis, principal component analysis) provide an effective mathematical tool to analyse large data sets in the presence of correlation and interdependencies
- the principle is an “optimal” transformation of the original data set to an orthogonal system containing identical information, accounting for (spectral) correlation
- leads to diagonalisation of the covariance matrix
- is a purely mathematically defined tool, not accounting for physical background represented by the data

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Principal Component Analysis (PCA)

- let $\text{Cov}\{L_j/\Delta L_j\}$, $j=1..N$, be the error normalised spectral covariance matrix of the data set, the principal components are computed as:

$$PC_k = \sum_{m=1}^N \frac{U_{km}(L_m - \bar{L}_m)}{\Delta L_m}$$

- where: PC_k - kth principal component, k from 1 to N
 N - number of spectral bands used in the original data set
 \underline{U}_k - kth eigenvector of the covariance matrix
 L_m - radiance in the mth spectral band
 \bar{L}_m - mean radiance value in the mth spectral band
 ΔL_m - noise-equivalent radiance, measurement error.
- Due to the transformation principle (diagonalisation of the covariance matrix) the PC are uncorrelated (orthogonal) and contain successively maximal information in the sense of signal variance:

$$\sigma_{PC_i}^2 > \sigma_{PC_j}^2 \text{ for } i > j$$

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PCA - SNR and Intrinsic Dimensionality

- Since the computation was done using error-normalised radiances, the eigenvalue gives directly the SNR of the corresponding PC:

$$\lambda_k = \text{SNR}^2(PC_k)$$

with λ_k being the kth eigenvalue of $\text{Cov}\{L_j/\Delta L_j\}$

- based on this we can define the **intrinsic dimensionality** of the analysed data set as:

$$D = \max(k) \text{ with } \sqrt{\lambda_k} > 1, D < N.$$

- The intrinsic dimensionality gives a measure, how many PCs contain significant information (in the sense of variance), i.e. are necessary to reconstruct the full information content of the original data set. It is, however, an unsharp definition.

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What does Intrinsic Dimensionality Tell Us?

- It tells us how many **statistically independent parameters** can be retrieved from the data set in principle (but not which ones and how!)
- it tells us whether the inverse task is solvable in general ($D \blacklozenge$ number of desired parameters)
- it **does not say**, that we need only D spectral channels, because:
each parameter retrieval from the spectral measurement can be seen as a statistical estimate \Rightarrow general rule: the larger the number of measurements, the higher the achievable accuracy!
- examples:
 - for simulated MOS-data (varying C, S, Y, τ_A, α) we get D up to 6
 - real MOS-data over water $D \sim 5$

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Appendix: Technical Parameters MOS-IRS

Parameter	MOS-A	MOS-B	MOS-C
Spectral Range [nm]	755 - 768	408 - 1010	SWIR
No. of Channels	4	13	1
Wavelengths [nm]	756.7; 760.6; 763.5; 766.4 O ₂ A-band	408; 443; 485; 520; 570; 615; 650; 685; 750; 870; 1010 815; 945 (H ₂ O- vapor)	1600
spectral halfwidth [nm]	1.4	10	100
Field of View			
along track x [deg]	0.344	0.094	0.14
across track [deg]	13.6	14.0	13.4
Swath Width [km]	195	200	192
No. of Pixels	140	384	299
Pixel Size x*y [km²]	1.57x1.4	0.52x0.52	0.52x0.64
Measuring Range			
Lmin [$\mu\text{Wcm}^{-2}\text{nm}^{-1}\text{sr}^{-1}$]	0.1	0.2	0.5
Lmax [$\mu\text{Wcm}^{-2}\text{nm}^{-1}\text{sr}^{-1}$]	40	65	18

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