The state of the earth: estimating physical parameters from noisy and incomplete earth observation data

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A

Supplementary information

A.1. PROSAIL inversion implementation details

A.1.1. Loss functions

When performing analyses on a loss landscape, the selection of an appropriate loss function (similarity metric d) can be of great importance. In the case of multispectral data, the simplest approach would be to consider all bands independently, and apply the mean absolute error (MAE) (or L_1 loss) function to compare the simulated spectrum $\hat{\mathbf{x}}$ and the observed spectrum $\mathbf{x}$ as:

$$MAE(\hat{\mathbf{x}}, \mathbf{x}) = \frac{1}{B} \cdot \sum_{b=0}^{B} |\hat{\mathbf{x}}_b - \mathbf{x}_b| \tag{A.1}$$

Here B is the number of bands in the spectrum. However, the values of spectral bands can greatly differ in magnitude, causing the MAE to be biased towards the bands with the greatest expected reflectance values (such as infrared). A relatively simple way to alleviate this problem is to use the proportional mean absolute error (PMAE), which is equivalent to the mean absolute percentage error (MAPE) used in other work [50], but does not convert the representation to percentages:

$$PMAE(\hat{\mathbf{x}}, \mathbf{x}) = \sum_{b=0}^{B} \frac{|\hat{\mathbf{x}}_b - \mathbf{x}_b|}{s_b} \tag{A.2}$$

MAE and PMAE are intuitive loss functions for the reconstruction of spectral data. However, in some applications, the brightness or albedo of a spectrum overall is less important than the ratio of band values compared to other band values, forming the hue of the spectrum. The spectral angle mapper (SAM) loss function [302] can be used to try to capture this aspect of a reconstruction, and can be computed as:

$$SAM(\hat{\mathbf{x}}, \mathbf{x}) = \arccos \frac{\hat{\mathbf{x}} \cdot \mathbf{x}}{(\hat{\mathbf{x}} \cdot \hat{\mathbf{x}}) * (\mathbf{x} \cdot \mathbf{x})} \cdot \frac{180}{\pi} \tag{A.3}$$

A.1.2. OPTIMISATION PROCEDURE

We treat the numerical optimisation procedure as a black-box optimisation problem. Within black-box optimisation algorithms, the tradeoff between *exploration* (identifying promising new parts of the search space) and *exploitation* (improving already known promising solutions until convergence) is often a central concept. In unimodal landscapes, only a single optimum exists, allowing greedy algorithms such as hill climbing or greedy local search (for an overview of stochastic local search methods, see [64]) to quickly converge to a local optimum, committing fully to exploitation. If the landscape is multimodal, there are multiple different local optima, causing greedy algorithms to get stuck in local optima. In this case, algorithms that add more exploration to their optimisation heuristics would be necessary.

Our experiments used greedy local search as an optimisation algorithm. For every instance, we initialised the current solution c to the mean of the prior distributions of the free parameters. At every optimisation step, we generated a candidate new solution $\boldsymbol{\theta}'$ by perturbing the elements of $\boldsymbol{\theta}$: $\boldsymbol{\theta}'_p = c_p + \mathcal{N}(0, \sigma_p)$, where p is a parameter in $\boldsymbol{\theta}$ and $\sigma_p = 0.05 \cdot \frac{max(p)-min(p)}{2}$. Here σ_p represents the intensity of the perturbation for a parameter p; we set it to 5% of the middle-way point of the parameter range (e.g., if a parameter ranges from 0 to 10, its perturbation intensity would be $0.05 \cdot \frac{10-0}{2} = 0.25$), though other mutation strategies could also be considered. If $\mathcal{L}(M(\boldsymbol{\theta}'), \mathbf{x}) < \mathcal{L}(M(\boldsymbol{\theta}), \mathbf{x})$, $\boldsymbol{\theta}'$ becomes the new $\boldsymbol{\theta}$. This procedure is iterated until the function evaluation budget has been exhausted.

Using greedy local search resulted in two main advantages. First, convergence will be fast, reducing the computational load of our experiments. Second, using a greedy algorithm allows us to test for multimodality (since the algorithm could converge to different optima when repeating an optimisation procedure), which is important to Section 5.4.1.

We note that, if the results for our experiments described in Section 5.4.1 indicate that PROSAIL inversion is a multimodal problem, a global optimisation method would need to be used to enable reliable convergence to a global optimum.

A.2. PROSAIL INVERSION: REAL-WORLD SENTINEL-2 DATA

Although our main experiments in Chapter 5 focussed on simulated data, since this allowed us access to both noise-free and noisy data, it is possible that there are other factors, beyond the Gaussian noise and spectral mixing we considered in Section 5.4.2, that result in ill-posedness for parameter retrieval using real-world data. To ensure that the patterns we found (well-posedness of PROSAIL inversion) hold for real-world data as well, we performed additional analyses on real-world data, as shown in Figure 5.6.

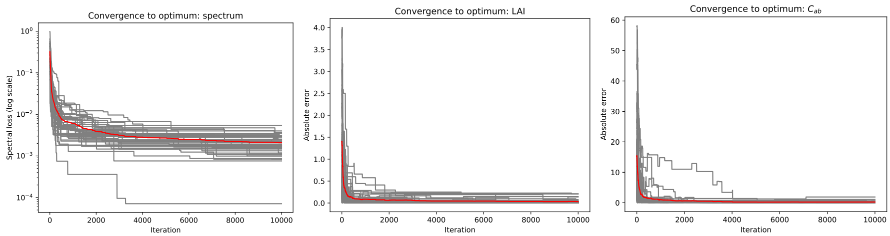
The Sentinel-2 dataset in question that we used was the SEN2-MSI-T cloud removal dataset from Chapter 4. While any Sentinel-2 Level-2A-based dataset would work, this dataset offered a convenient mix of scale and diversity. The dataset consists of 5 land cover classes, each split into a geographically diverse set of 4 scenes, resulting in 20 total locations. Every scene contained a cloud-free observation at 5 time steps within a period of 6 months, resulting in a total of 100 geospatially- and temporally diverse images. From each image, we took the centre pixel as the representative spectrum for the image (using multiple pixels from the same image could have biased the evaluation to the specific images of the dataset). Therefore, this dataset enabled us to evaluate on a curated, diverse set of 100 real-world instances and check if the PROSAIL inversion loss landscapes were still well-posed.

B

Additional results

B.1. PROSAIL inversion

B.1.1. Optimisation convergence



(a) Spectral loss function (b) LAI retrieval loss (c) C_{ab} retrieval loss

Figure B.1: Visualisation of convergence to a stable solution based on the spectral loss function (B.1a), the retrieval loss for LAI (B.1b), and the retrieval loss for C_{ab} (B.1c). In these plots, every gray line represents a randomly sampled instance from D, and the red line represents the mean of these runs. Out of the free parameters in our experiments, LAI took longer than other parameters to converge, but still did so within the budget limit. On average (the red lines), the parameters converged to stable values within 1000 iterations, with later iterations only slightly improving the spectral loss further.

We performed this additional experiment to verify that the function evaluation budget used in our experiments is sufficient to converge to a stable optimum, both in terms of the spectral loss value and the parameters of the configuration $\boldsymbol{\theta}$. We performed our optimisation approach on 100 random instances, and plotted the loss values for the spectrum (which the optimisation algorithm uses to perform

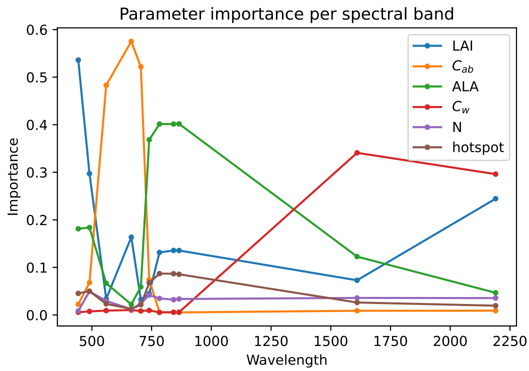


Figure B.2: Relative importance of different parameters for different wavelengths. Every point on a line represents the average importance of the parameter of that line in determining the MAE for a particular spectral band's wavelength.

optimisation) and for the retrieved parameters in the configuration (which the algorithm does not have access to, and is plotted for evaluation purposes). A very low rate of improvement for later iterations would indicate that the budget is sufficient to converge to a stable optimum.

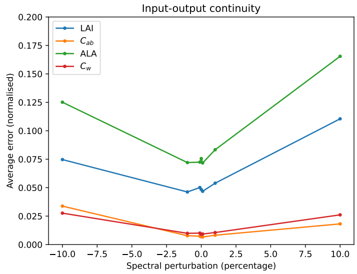
The results of this experiment can be found in Figure B.1. As the figure shows, the function evaluation budget allotted to the optimisation algorithm is sufficient to converge to stable values on average, and a convergence of the spectral loss (Figure B.1a) corresponds to a convergence of the retrieval losses of individual parameters (Figures B.1b and B.1c). As a result, our experimental setup appears to be well suited to answer our research questions.

B.1.2. Parameter importance per band

In addition to our main parameter importance experiment, we computed the importance of 6 of the globally most important parameters at every Sentinel-2 band, and plotted this is Figure B.2. As can be seen in the figure, the relative importance of the parameters can vary greatly between spectral bands. Therefore, parameters with a relatively low global importance may still be relatively easily retrievable, due to the sensitivity of the loss landscape to these parameters in local, specialised parts of the parameter space. All parameters from our selection have a part of the spectrum where they have the highest impact (LAI for ultraviolet and blue, chlorophyll for green, red and near-infrared, leaf angle for short-wave infrared, and leaf water content for infrared).

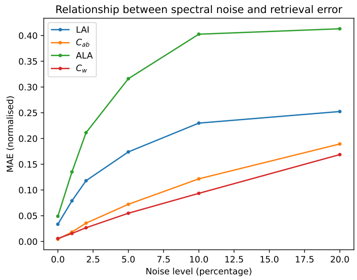
B.1.3. PROSAIL INVERSION SAM RESULTS

These supplementary figures contain the results for our experiments for the SAM loss function, corresponding to the same analyses we provide in Section 5.5 for the PMAE loss function. We have moved these figures to the supplementary material because their patterns largely conformed to those for PMAE. Figure B.3 contains results for Experiment 2, Figure B.4 contains results for Experiment 3, Table B.1 contains results for Experiment 4, and Table B.2 contains results for Experiment 5.



(a) Shift per perturbation

Figure B.3: The continuity of the output for PROSAIL inversion (predicted configuration $\hat{\boldsymbol{\theta}}$) with respect to perturbations to the input (spectrum), aggregated over all 1000 instances and normalised to a 0-1 range based on the bounds of the parameter range. Unlike in the PMAE results, the best solution for no perturbation (0 on the x-axis) did not have a near-zero error rate for LAI and ALA; this suggests that SAM may not be an appropriate choice as an optimisation loss function.



(a) Performance per noise level

Figure B.4: The impact of spectral noise on retrieval performance, aggregating the 'shifted optimum' phenomenon over all 1000 instances, showing that it is a consistent pattern, and the intensity of the shifts increases as the noise level increases.

Parameter	Normalised MAE target			
	$\alpha_1\boldsymbol{\theta}_1^+ + \alpha_2\boldsymbol{\theta}_2^+ + \alpha_3\boldsymbol{\theta}_3^+$	$\boldsymbol{\theta}_1^+$	$\boldsymbol{\theta}_2^+$	$\boldsymbol{\theta}_3^+$
LAI	0.136 ± 0.167	0.199 ± 0.182	0.203 ± 0.187	0.206 ± 0.19
C_{ab}	0.057 ± 0.058	0.128 ± 0.113	0.121 ± 0.109	0.123 ± 0.11
ALA	0.24 ± 0.172	0.296 ± 0.233	0.299 ± 0.241	0.307 ± 0.233
C_w	0.043 ± 0.053	0.082 ± 0.069	0.084 ± 0.072	0.087 ± 0.073

Table B.1: Results for E4 on the impact of spectral mixing. Every cell represents the (normalised) MAE between the optima found for the mixed spectrum $\mathbf{x}'$ and the quantities listed in the columns. The first column represents the weighted mean of the true configurations of the constituent spectra $\mathbf{x}_1$, $\mathbf{x}_2$ and $\mathbf{x}_3$, while the other columns represent the MAE compared to these individual constituent configurations. This suggests that the solution for mixed spectra matches the weighted mean of the constituent configurations more closely than the configuration of any individual constituent spectrum.

Range interval	LAI prior range interval size				
	0%	**10%**	**30%**	**50%**	**100%**
LAI (uniform)	[1]0.0 ± 0.0	[2]0.473 ± 0.289	[3]1.413 ± 0.863	[4]2.214 ± 1.37	[5]2.978 ± 2.124
LAI	[1]0.0 ± 0.0	[2]0.755 ± 0.33	[3]1.606 ± 1.054	[4]1.995 ± 1.572	[5]2.151 ± 1.851
C_{ab}	[2]10.86 ± 15.61	[1]10.35 ± 15.497	[3]11.455 ± 15.626	[4]12.084 ± 15.965	[5]12.23 ± 16.092
ALA	[1]24.908 ± 22.832	[2]30.773 ± 22.476	[3]34.7 ± 23.514	[4]35.712 ± 24.424	[4]35.725 ± 24.357
C_w	[1]0.004 ± 0.007	[1]0.005 ± 0.007	[3]0.005 ± 0.008	[4]0.005 ± 0.008	[5]0.005 ± 0.008

Table B.2: Mean absolute error rates for parameter retrieval performance for the four different parameters (rows), with columns representing the interval size of a range constraint prior on LAI (with 100% covering the full original parameter range). The 'LAI (uniform)' row represents the performance of estimating LAI through uniform random sampling, while in other columns, performance is acquired through optimisation. In each row, the prior range size in a column marked with a lower number (e.g., [1]) retrieves a parameter significantly better (significance level $\alpha = 0.05$) than one with a higher number (e.g., [2]). Adding range constraint priors on LAI greatly improved LAI retrieval performance, while also improving ALA (but not C_{ab} and C_w) retrieval performance.

B.2. EMMI

B.2.1. ϵ-MANIFOLD EFFECTIVENESS WITH PRECISION AND RECALL

Dataset	ϵ-manifold		Uncertainty quantification	
	Precision	Recall	Precision	Recall
PROSAIL	1.0	1.0	1.0	0.68
PROSAIL 2D	0.94	0.38	1.0	0.48
TP	0.99	0.6	1.0	0.24
Lorenz63	0.99	0.8	0.85	0.3
GM	0.81	0.94	0.99	0.79
TM	0.96	0.98	0.87	0.56
LR	0.82	0.94	1.0	0.52

Table B.3: Results for the oracle-based ϵ-manifold validation experiment for RQ2, showing precision and recall scores for a classification task where, for every instance, the true values $\boldsymbol{\theta}^+$ had to be predicted along with a negative sample from the validation points. For these metrics, only a single score could be computed.

B.2.2. EMMI RESULTS WITH PRECISION AND RECALL

Table B.4: Precision of the different methods approximating the ϵ-manifolds, with all hyperparameters for all methods (including the appropriate eMMI variant) automatically determined through hyperparameter optimisation. For every simulator, the best performance has been marked in **boldface**, with statistical significance determined by a Wilcoxon signed-rank test at significance level $\alpha = 0.05$.

Method	PROSAIL	PROSAIL 2D	TP	Lorenz63	GM	TM	LR
RF	0.67 ± 0.46	0.57 ± 0.37	$\mathbf{0.89 \pm 0.12}$	0.51 ± 0.15	0.91 ± 0.17	0.38 ± 0.37	0.05 ± 0.22
GP	0.75 ± 0.09	0.58 ± 0.13	0.51 ± 0.03	0.5 ± 0.0	$\mathbf{1.0 \pm 0.01}$	0.5 ± 0.0	0.5 ± 0.0
BNN	0.51 ± 0.09	0.67 ± 0.15	0.51 ± 0.03	0.5 ± 0.0	0.58 ± 0.13	0.5 ± 0.0	0.5 ± 0.0
ABCSMC	0.34 ± 0.31	0.37 ± 0.32	0.38 ± 0.32	0.37 ± 0.24	0.27 ± 0.38	0.32 ± 0.33	0.42 ± 0.48
TabPFN	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
eMMI	$\mathbf{0.84 \pm 0.1}$	$\mathbf{0.86 \pm 0.12}$	0.9 ± 0.12	$\mathbf{0.59 \pm 0.2}$	1.0 ± 0.0	$\mathbf{0.68 \pm 0.14}$	$\mathbf{0.96 \pm 0.1}$

Method	PROSAIL	PROSAIL 2D	TP	Lorenz63	GM	TM	LR
RF	0.09 ± 0.11	0.15 ± 0.16	0.01 ± 0.01	0.03 ± 0.02	0.84 ± 0.23	0.27 ± 0.37	0.0 ± 0.0
GP	0.67 ± 0.21	0.7 ± 0.22	$\mathbf{0.97 \pm 0.11}$	1.0 ± 0.01	0.26 ± 0.24	$\mathbf{1.0 \pm 0.0}$	1.0 ± 0.0
BNN	0.93 ± 0.2	0.85 ± 0.27	$\mathbf{0.98 \pm 0.08}$	$\mathbf{1.0 \pm 0.0}$	$\mathbf{0.85 \pm 0.29}$	$\mathbf{1.0 \pm 0.0}$	$\mathbf{1.0 \pm 0.0}$
ABCSMC	0.34 ± 0.37	0.44 ± 0.41	0.32 ± 0.33	0.35 ± 0.32	0.16 ± 0.29	0.4 ± 0.44	0.0 ± 0.0
TabPFN	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0
eMMI	$\mathbf{0.95 \pm 0.19}$	$\mathbf{0.96 \pm 0.07}$	0.86 ± 0.26	0.43 ± 0.3	$\mathbf{0.95 \pm 0.14}$	0.98 ± 0.12	0.79 ± 0.25

Table B.5: Recall of the different methods approximating the ϵ-manifolds, with all hyperparameters for all methods (including the appropriate eMMI variant) automatically determined through hyperparameter optimisation. For every simulator, the best performance has been marked in **boldface**, with statistical significance determined by a Wilcoxon signed-rank test at significance level $\alpha = 0.05$.

Acknowledgements

After all the "academic we" that you, as the reader, have just endured, it seems only fitting that this short section can provide some relief in favour of a more personal touch. After four years of working as a PhD, I certainly understand now why everyone feels the need to add these acknowledgements: so much in how a PhD is experienced depends on the people who support it.

In this vein, the first people to thank are my supervisors. Mitra, you are clearly doing something right, because even after working together since 2019 I still enjoy the process, and constantly learn from you. Thank you for all the opportunities you have given me that I have gladly taken, and for being the kind of supervisor who makes academia both a safe and pleasant experience for PhD students, and a stimulating environment to learn and grow. Peter, thank you for guiding me in the scary foreign place that is "the domain", and for the unfailingly kind and patient welcome I received in it. At times I nearly forgot I had work to do as I learned about concepts in biology and ecology, and to this day, I continue to read about these topics out of general interest. Holger, your views on AI, science and Europe are inspiring and closely match my own ideals, therefore finding very fertile soil in my brain. I suspect that my newfound hobby of following your social media posts, which bring some much-needed reality checks to the business influencer-dominated public discourse on AI, will remain a highly enjoyable passtime for the foreseeable future.

I would like to express my gratitude to everyone in the ADA research group, especially my fellow PhDs. I have learned much from you, from the excellent examples I could look up to when I joined as a Master student to the new students newly introduced to the group. In a vaguely chronological order: Jan, Koen, Marie, Anna, Can, Jeroen, Matthias, Bram, Mike, Annelot, Maedeh, Samira, Hadar, Thijs, Andreas, Khashayar, Inês, Nansheline and Sietse. A special mention should go to Julia, who was the first Master student I ever supervised (feeling woefully underqualified for the task as a fresh PhD), and not soon after, became the one colleague-PhD with whom I could jointly commiserate over the frustrations of working with EO data as an AI researcher. Also thanks to the part of ADA at RWTH Aachen, whom I always feel like I should find ways to spend more time with, and all the Master and Bachelor students who have come and gone (I'm sorry, there are just so many of you!).

Thank you to Alistair for being my guide during my research visit to ϕ-lab at

ESA, both in terms of work and in terms of cool slightly hidden vegan restaurants in the middle of Rome. Thanks also to James and Athanasia for their involvement when they were my contacts at ESA. Thanks to Juhuhn, my friend from back in our Master student days, with whom my research trajectory always seems strangely, but enjoyably, synced.

I tend to be more reserved when it comes to my private life, but the brevity of this paragraph should not be misinterpreted as it being the least important category. My work brings me satisfaction, which I appreciate a great deal. However, my happiness stems from my family and my partner Areum, which deserves more thanks than can be expressed through this public medium.

Curriculum Vitæ

Laurens Arp was born on 23 January 1995 in Haarlem, The Netherlands. He pursued his Bachelor studies at Vrije Universiteit Amsterdam, where he studied Lifestyle Informatics, followed by his Master studies in the Artificial Intelligence specialisation of Computer Science at Leiden University. He carried out his Master thesis with the ADA research group at Leiden Institute of Advanced Computer Science (LIACS), supervised by Dr. Mitra Baratchi, and graduated in 2020. After this, he kept working with the ADA group as a PhD candidate supervised by Dr. Mitra Baratchi and Prof.dr. Holger Hoos from LIACS, and Prof.dr. Peter van Bodegom from the Institute of Environmental Sciences (CML). During this time he also collaborated closely with research fellows from the European Space Agency (ESA), and spent time as a visiting researcher at the ϕ-lab at the European Space Research Institute (ESRIN) location of ESA in Frascati, Italy.

Laurens' interests lie in interdisciplinary work where typical machine learning assumptions are violated, particularly for relevant spatio-temporal problems such as environmental challenges, urban planning and socio-economic conditions, which often involves Earth observation data. He is currently working as a postdoctoral researcher at Leiden University, researching causal machine learning for spatio-temporal data. During his PhD studies, he took various AI courses at the European Summer School on AI (ESSAI) and Advanced Course on Artificial Intelligence (ACAI) in Ljubljana, in addition to courses on transferable skills such as project management, oral presentation skills and scientific conduct, among others.

List of Publications

Under Review

🗎 1. **Laurens Arp**, Peter van Bodegom, Nguyen Dang, Alistair Francis, Holger H. Hoos, and Mitra Baratchi. Inference from Noisy Observations through Model Inversion: Constructing ϵ-Manifolds of Potentially Valid Solutions. Under review.

2026

🗎 1. **Laurens Arp**, Peter van Bodegom, Holger H. Hoos, and Mitra Baratchi. Characterising the Ill-posedness of PROSAIL Inversion for Biophysical Paramter Retrieval. In *European Journal of Remote Sensing*, 59(1).

2024

🗎 2. **Laurens Arp**, Holger H. Hoos, Peter van Bodegom, Alistair Francis, James Wheeler, Dean van Laar, and Mitra Baratchi. 2024. Training-free thick cloud removal for Sentinel-2 imagery using value propagation interpolation. In *ISPRS Journal of Photogrammetry and Remote Sensing*, 216.

1. Julia Wąsala, Suzanne Marselis, **Laurens Arp**, Holger Hoos, Nicolas Longépé and Mitra Baratchi. 2024. AutoSR4EO: An AutoML Approach to Super-Resolution for Earth Observation Images. In *Remote Sensing*, 443.

2022

🗎 1. **Laurens Arp**, Mitra Baratchi, and Holger H. Hoos. 2022. VPint: value propagation-based spatial interpolation. In *Data Mining and Knowledge Discovery*, 36.

🗎 Included in this Thesis.

Glossary

automated algorithm configuration an optimisation problem where the hyperparameters of algorithms are automatically tuned based on an objective function 23

AutoML automated machine learning: automated model selection and algorithm configuration for machine learning problems 23

band a data dimension for an EO image containing measurements for a specific variable 13

black-box optimisation a type of optimisation problem/algorithm in which only the inputs and outputs of an objective function g can be observed, with no knowledge about g itself 22

configuration a vector $\boldsymbol{\theta}$ containing concrete value assignments for the physical parameters P 1, 22

convolutional neural network a type of neural network where local spatial patterns are extracted using convolutional kernels 32

data product a dataset containing estimations for quantities of interest through the processing of EO data 13

Earth Observation data obtained through sensors observing the Earth 11

hybrid model a machine learning model trained on the inverse of simulated data produced by an RTM 20

hyperspectral spectral (optical) data containing many spectral bands 16

ill-posed a problem that does not meet the requirements of well-posedness 21

in-situ direct measurements of relevant physical parameters 12

inference the estimation of the properties that generated an observed outcome 2

Landsat satellites operated by NASA, many of which contain a spectrometer as a sensor 15

look-up table a tabular dataset generated by an RTM, containing generating parameters and simulated outcomes 20

loss landscape a surface in $d+1$-dimensional space describing the loss function value of every point in the parameter space 101

model inversion the inversion of a (simulation) model capturing the data generation process for an inference problem 19

MODIS optical satellites operated by NASA with a high temporal resolution and a low spatial resolution 15

multispectral spectral (optical) data containing multiple spectral bands, often including wavelengths outside the visible ranges 15

optical data data containing measurements of a light spectrum 15

parameter estimation an inference setting where the value of a physical parameter p must be inferred from some observed feature data $\mathbf{x}$ 2

parameter space (search) space of the parameter domain D_P containing all possible combinations of parameter values 100

physical parameter a variable p in a set of scientific variables P describing the state of a physical system 1

PROSAIL a radiative transfer model for vegetation, combining the PROSPECT and 4SAIL models 19

radiative transfer model a type of physical model that simulates a light spectrum based on physical input parameters 19

remote sensing data obtained remotely by sensors not directly interacting with the object being observed 13

search space space containing all possible combinations of parameter values, through which we must perform a search to find an optimum 22

sensor network a spatially distributed network of sensors, measuring a target variable at specific points 12

Sentinel-2 multispectral optical satellites operated by ESA 15

spatial interpolation filling in a spatial grid of missing values in between of a number of known measurements 27

spectral band a measurement of light intensity for a single wavelength on a light spectrum 15

spectrometer an optical sensor measuring light intensity at certain wavelengths 15

swath width of a remote sensing sensor passing over a study area 13

VPint our proposed spatial interpolation algorithm founded on a system-oriented perspective 33

VPint2 our proposed spatial interpolation algorithm suitable for filling in gaps in optical satellite imagery 66