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Valuation of Calibration for Satellite Constellations

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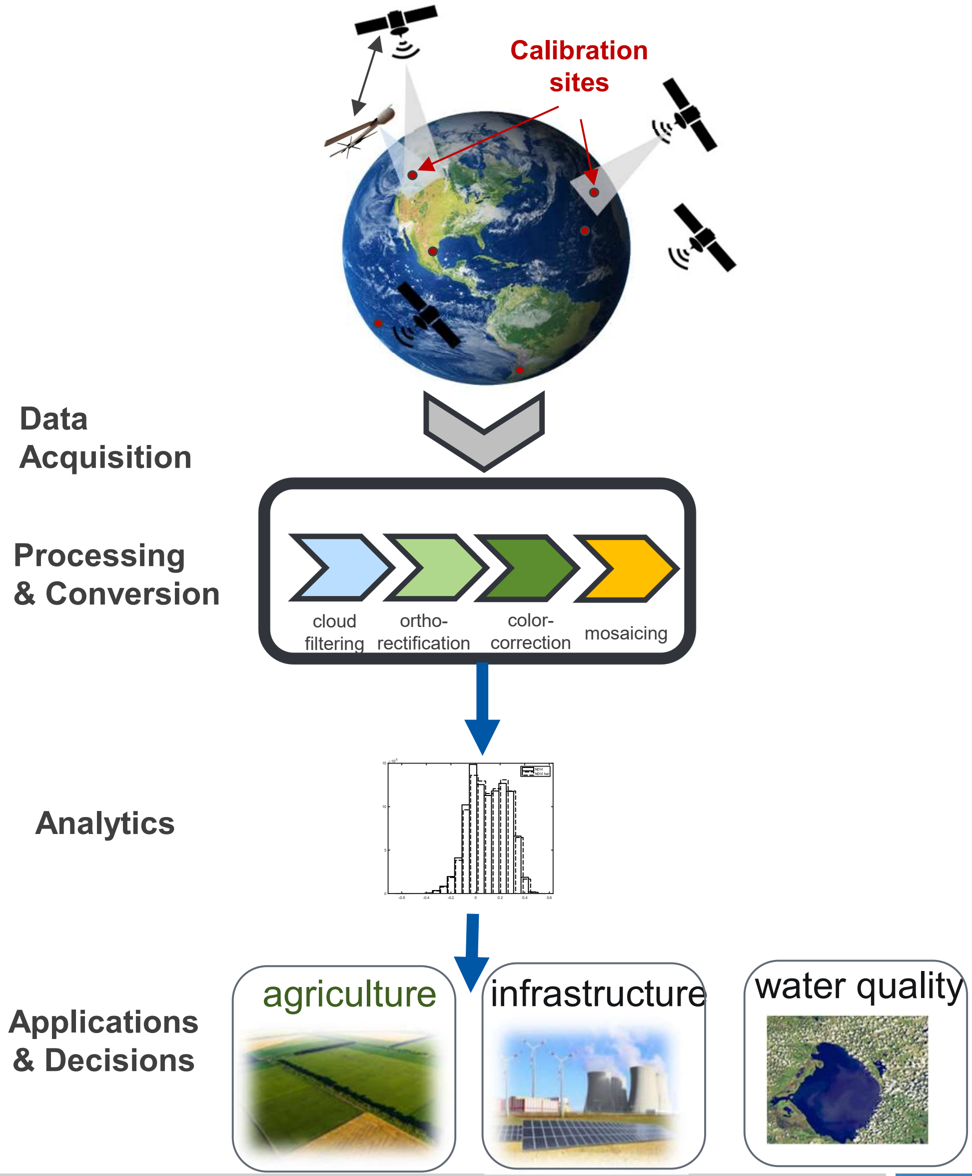
Frequent calibration is increasingly important for satellite constellations

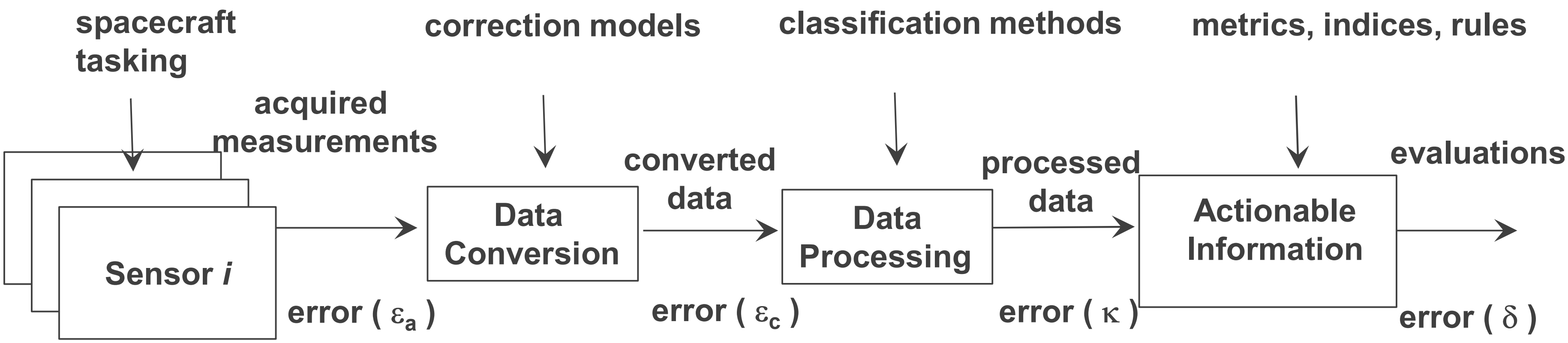
- Use of EO data from small satellites is rapidly increasing, but there are important challenges in its accuracy and reliable use.

- Calibration is important for new systems with several sensors or multi-platform systems that combine space-based and air-based observation platforms.

- Intercalibrations with larger spacecraft has limitations as it requires consistency of spectral bands, spatial collocation, and consistency of viewing geometry.



Modeling Value of Calibration in Remote Sensing



Acquisition **Conversion**

Effective Data Acquired (EDA)
(Data quantity adjusted by quality)

Modeling & Classification

Error propagation, non-linear impacts due to thresholds

Evaluation & Decisions

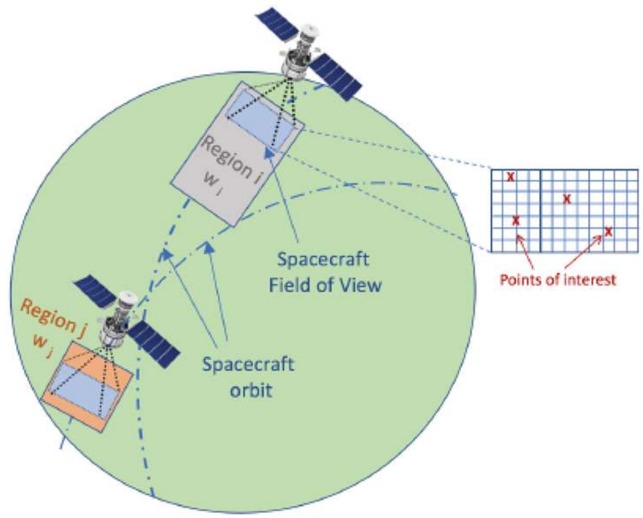
Value of information (difference in economic outcomes)

Return on Investment for use of calibration services for Data Providers

Architecture Value Proposition for Earth Observing Systems for Science Missions

The value delivered by a specific system architecture is directly related to the *useful scientific data provided by the system* for the regions of interest over its lifecycle.

→ Total scientific data returned serves as a proxy for architecture value.



Siddiqi, A., Magliarditi, E., and de Weck, O. L., "Valuing New Earth Observation Missions for System Architecture Trade Studies"" IEEE International Geoscience and Remote Sensing Symposium, (2019)

Data acquired is quantified for each target region and adjusted for data quality

$$EDA\ of\ Target\ Region\ k:\quad EDA_k = \sum_{j=1}^{S}\sum_{i=1}^{I_j} Q_{ij}{}^{k}\, \overbrace{\frac{\mu_{ij}{}^{k}}{\sigma_{ij}{}^{k}}}^{\text{Inverse of Coefficient of Variation of quality metric (SNR)}}$$

$$V = \sum_{k=0}^{n} \frac{EDA_k \times \omega}{(1+r+r_\varepsilon)^k} - \sum_{k=0}^{n} \frac{Cost_k}{(1+r)^k}$$

r_ε is an additional discount factor associated with quality based on calibration

$$r_\varepsilon = a(t - t_i)$$

r_ε is modeled to be small after each calibration event at time t_i

$Cost_k$ is monetary cost incurred in period *k*
ω is a monetizing parameter in dollars per bits
r is a discount ratio, and *n* is the total number of time periods

Siddiqi, A., Magliarditi, E., and de Weck, O. L., "Valuing New Earth Observation Missions for System Architecture Trade Studies""
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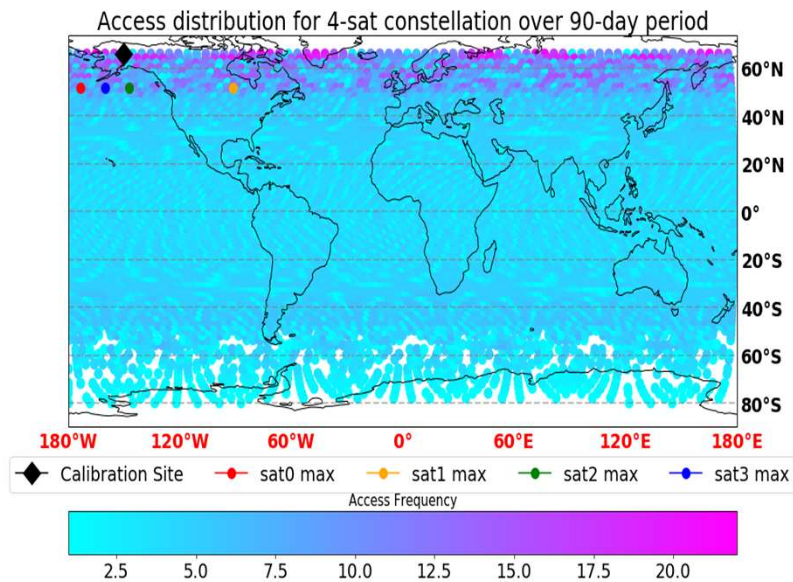
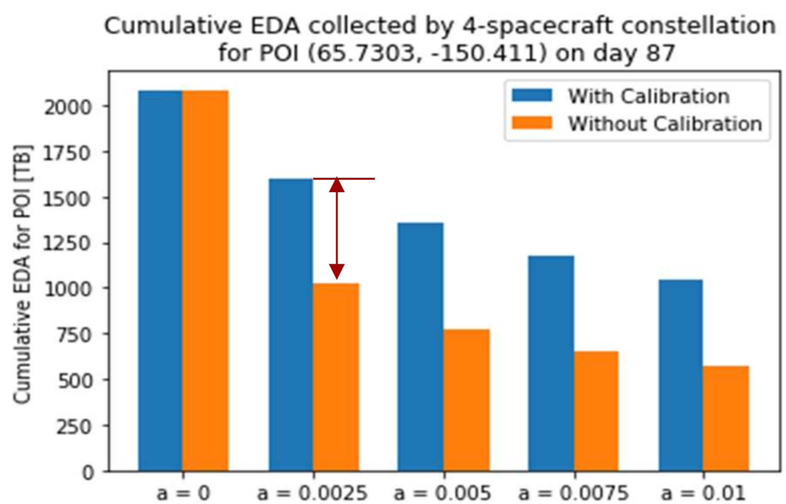
Quantifying impact of calibration with difference in constellation EDA

- Cubesat constellation of 4 spacecraft with passive imaging sensors (same specs as shown in previous case)
- -90 day simulation
- Terrestrial calibration sites to be located below 66.5deg

- Four sites, below 66.5° latitude were identified to have the highest access frequency (marked in red, blue, green and yellow)
- The site in black diamond was assumed to be the calibration site. This site (located at 65.7303, -150.411 near Fairbanks, Alaska
- Comparison between calibration and no calibration cases shows, for a=0.25%, adjusted EDA of ~1000 TB without calibration and ~1600 TB with calibration, i.e. a 60% increase in EDA if calibration is performed.





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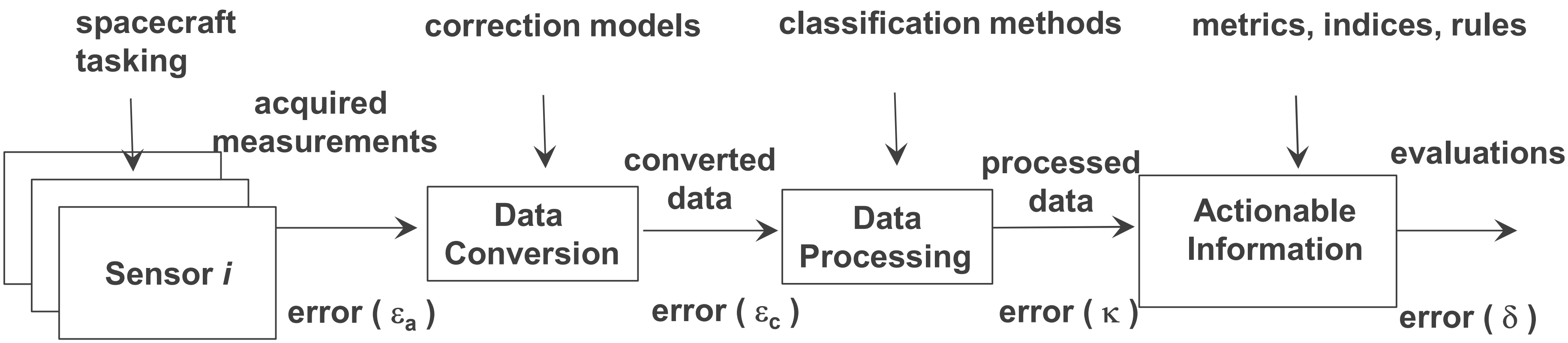
Modeling Value of Calibration in Remote Sensing



Acquisition Conversion	Modeling & Classification	Evaluation & Decisions
Effective Data Acquired (EDA) (Data quantity adjusted by quality)	Error propagation, non-linear impacts due to thresholds	Value of information (difference in economic outcomes)

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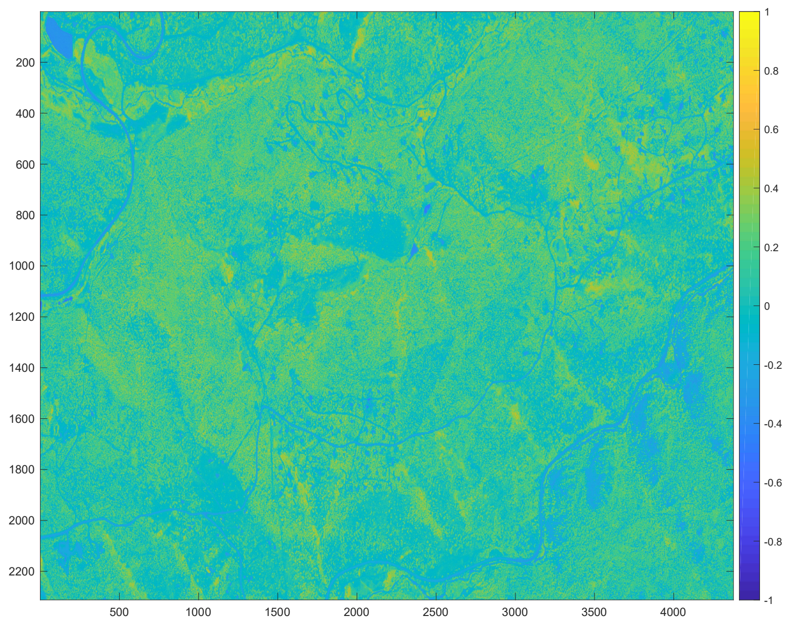
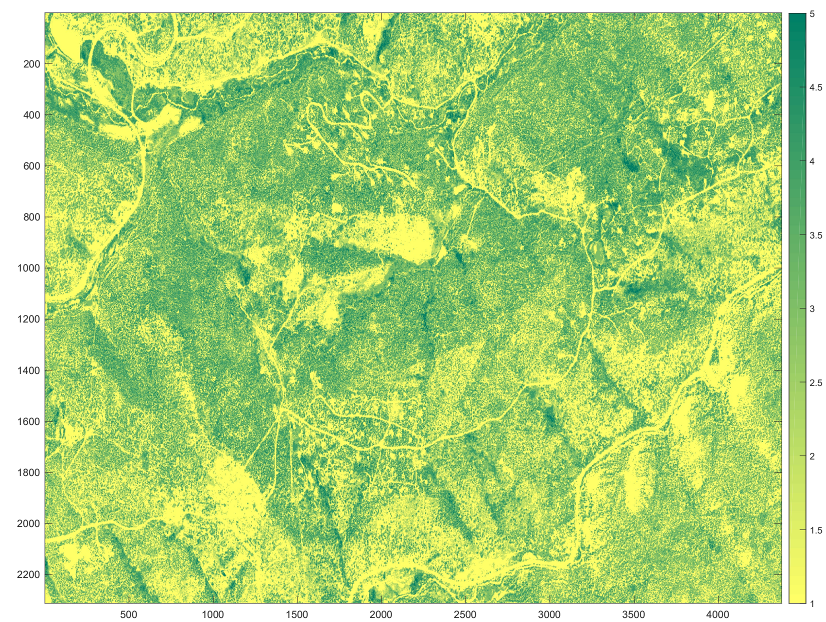
Example Case: NDVI analysis

NDVI



Classified NDVI



Cold Springs, Colorado
NAIP imagery data, 2015

1m ground pixel resolution

Leica Geosystem's
ADS100/SH100 digital sensors

class 1: NDVI < 0	No Vegetation
class 2: $0 \leq$ NDIV < 0.1	Bare Area
class 3: $0.1 \leq$ NDVI < 0.25	Low Vegetation
class 4: $0.25 \leq$ NDVI < 0.4	Moderate Vegetation
class 5: NDVI ≥ 0.4	High Vegetation

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} = \frac{SR - 1}{SR + 1} \qquad SR = \frac{\rho_{NIR}}{\rho_R}$$

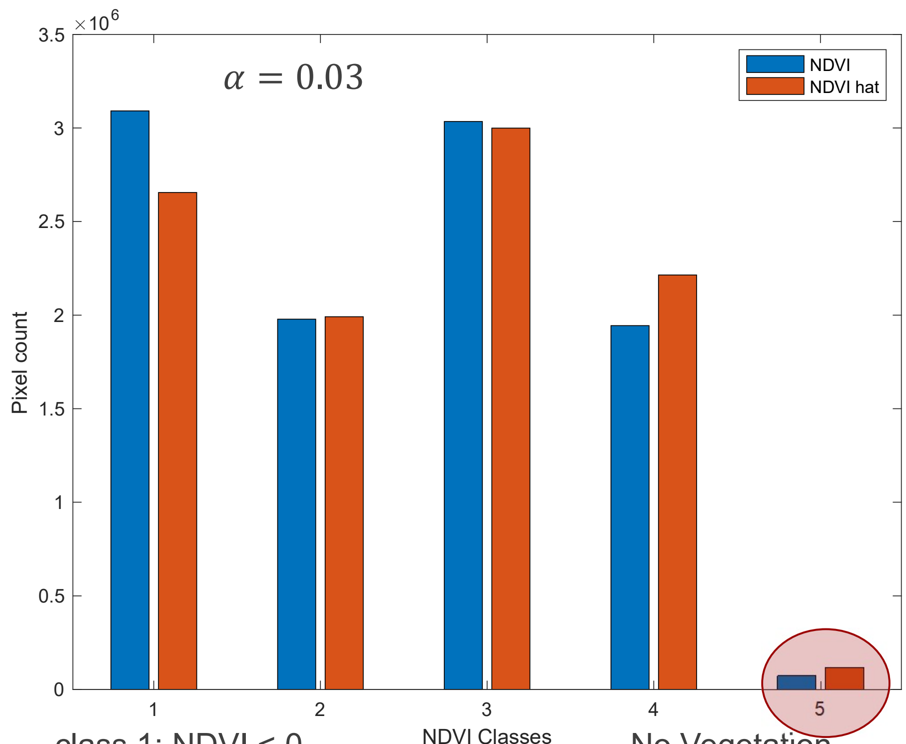
Siddiqi, A., Baber, S., de Weck, O. L., and Durell, C., "Error and Uncertainty in Earth Observation Data Value Chains", IEEE IGARSS 2020

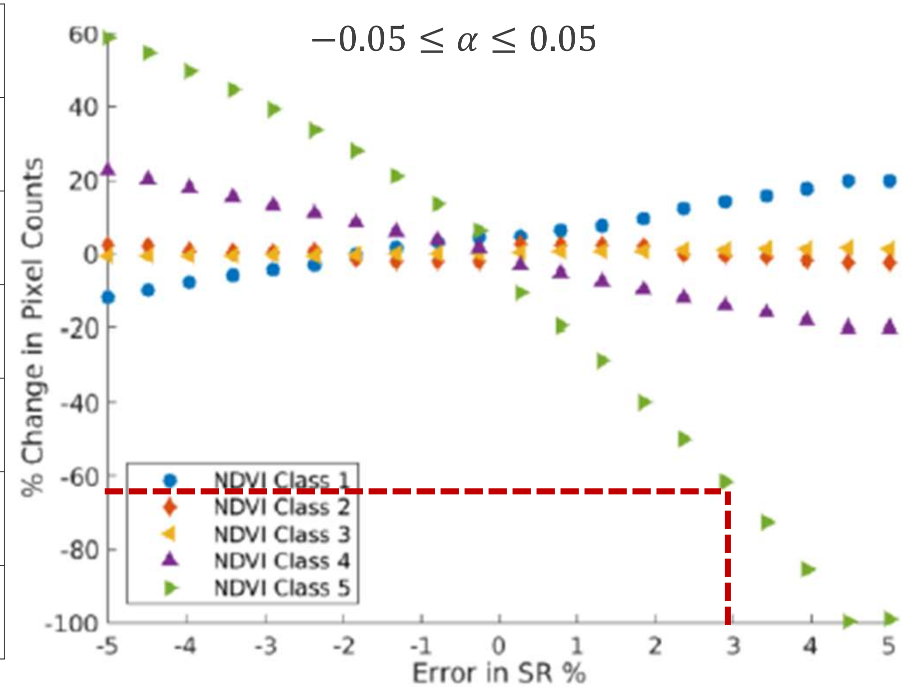
NDVI classification: Discrete thresholds can create large non-linear impacts

Assume the spectral ratio, $\widehat{SR}$, is simply:

$\widehat{SR} = SR(1+\alpha)$

*parameter α aggregates all the error parameters

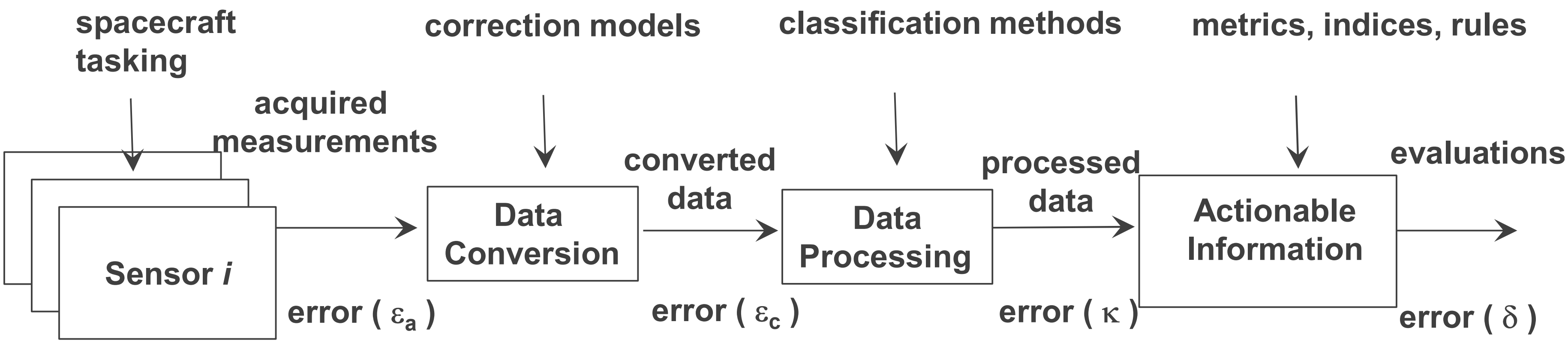




class 1: NDVI < 0	No Vegetation
class 2: 0 ≤ NDIV < 0.1	Bare Area
class 3: 0.1 ≤ NDVI < 0.25	Low Vegetation
class 4: 0.25 ≤ NDVI < 0.4	Moderate Vegetation
class 5: NDVI ≥ 0.4	High Vegetation

A 3% error in SR leads to a -60% change in class 5 pixel count in this case

Modeling Value of Calibration in Remote Sensing



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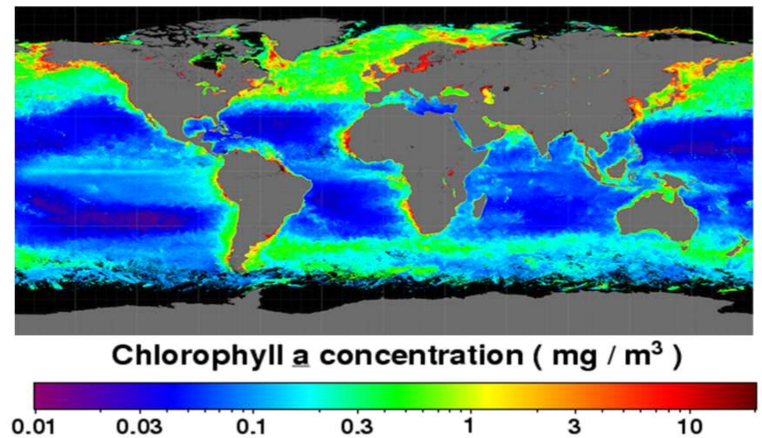
Remote Sensing of Harmful Algal Blooms

- Remote sensing methods primarily focus on the **pigments** of HABs groups
- Pigments **do not** indicate **toxicity** of algal blooms (requires laboratory testing)

- **Advantages**:
  - Temporal resolution
  - Early detection
  - Spatial precision
  - Prediction



MODIS Aqua `chlor_a` seasonal composite spring 2014 (NASA OBPG)

$$log_{10}(chlor_a) = a_0 + \sum_{i=1}^{4} a_i \left(log_{10}\left(\frac{R_{rs}(\lambda_{blue})}{R_{rs}(\lambda_{green})}\right)\right)^i$$

Neurotoxic Shellfish Poisoning

Cell counts > 5000 / L leads to shellfish harvesting closure

The fall 2018 bloom is reported to have cost businesses $150 million

Can take weeks after a bloom for shellfish to become safe for consumption.

O'Reilly, J. E., Maritorena, S., Mitchell, B. G., Siegel, D. A., Carder, K. L., Garver, S. A., ... & McClain, C. (1998). Ocean color chlorophyll algorithms for SeaWiFS. *Journal of Geophysical Research: Oceans*, *103*(C11), 24937-24953.

Discrete thresholds for water quality are used

There is no federally binding threshold for cyanobacteria in recreational freshwater lakes or river in the United States.

World Health Organization (WHO) maximal acceptable concentration of microcystin-LR in drinking water: 1 µg / L

States generally develop their own thresholds for levels of action.

Table 2. Numeric Thresholds for Cyantoxins in Recreational Water.

Threshold (µg/L)	Microcystins*	Anatoxin-a	Cylindrospermopsin	Saxitoxins*
Informational Sign	<6	<80	<5	<0.8
Recreational Public Health Advisory	6	80	5	0.8
Elevated Recreational Public Health Advisory	20	300	20	3

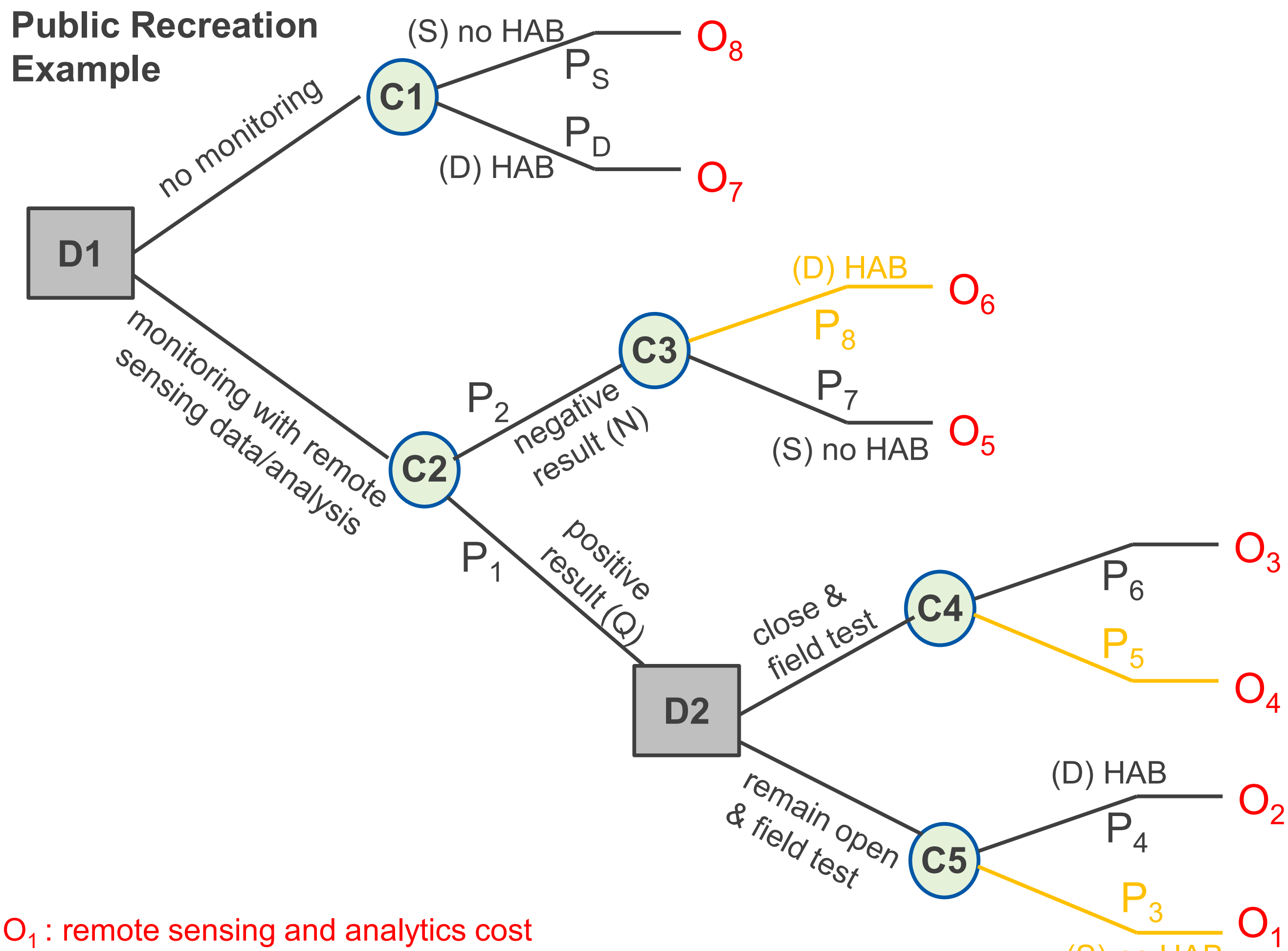
*Microcystins and saxitoxin thresholds are intended to be applied to total concentrations of all reported congeners of those cyanotoxins.

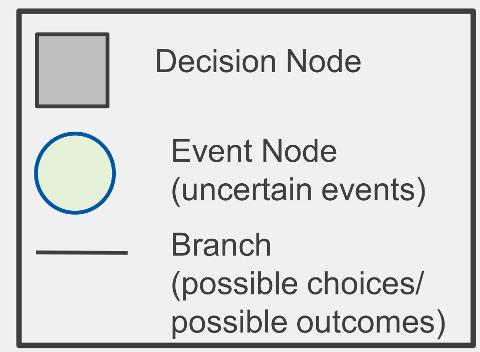
State of Ohio cyanotoxin thresholds

Warning and Danger HABs signage from Ohio.

WHO. (1998). Guidelines for drinking water quality. Geneva: World Health Organisation
Kasich, J., et al. (2016). State of Ohio Harmful Algal Bloom Response Strategy for Recreational Waters.

Decision analysis can be used for comparing economic outcomes and remote sensing value with different data quality





Expected value of event node *i*:

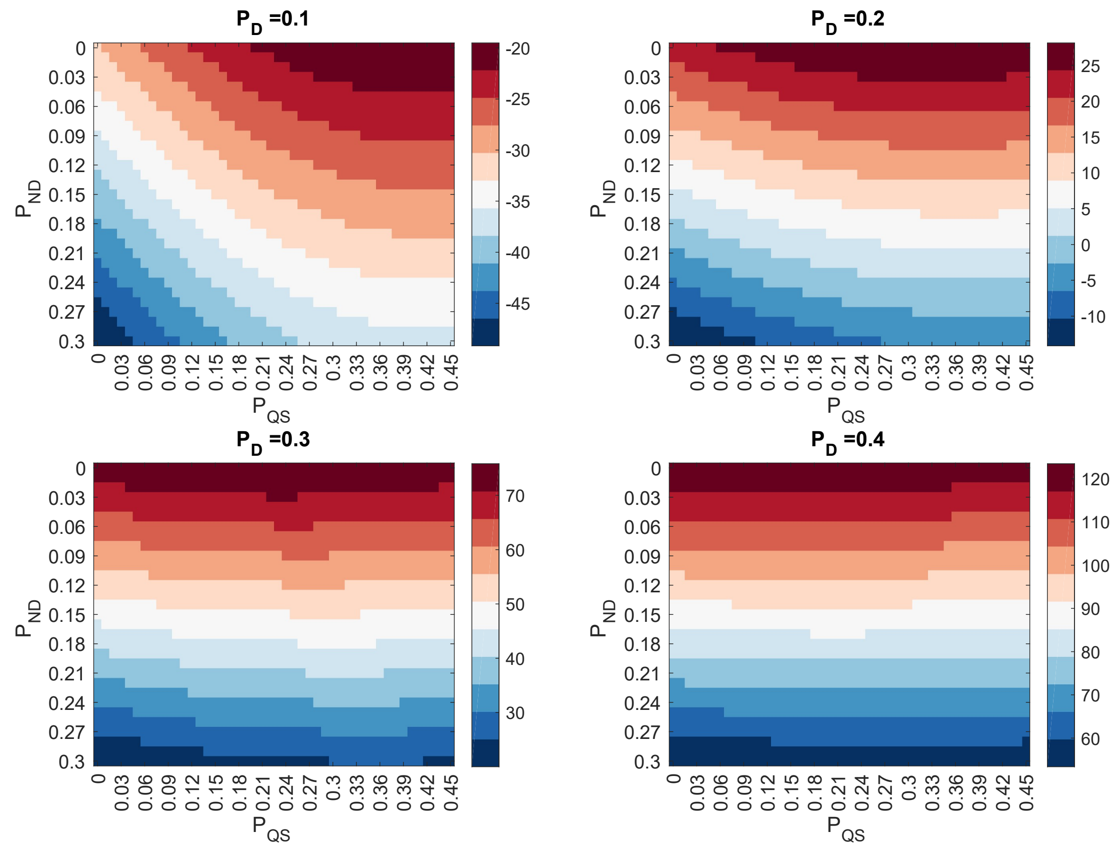
$$E_i(V) = \sum_{k=1}^{n} p_k O_k$$

O_1 : remote sensing and analytics cost
O_2 : health care costs due to exposure+ remote sensing and analytics cost
O_3 : health care costs due to exposure+ loss of park fees+ remote sensing and analytics cost
O_4 : loss of park fees+ remote sensing and analytics cost

Data quality will impact likelihood of false positive and false negatives and will impact decision value

- Three variables used to evaluate difference of decisions :
  - **P_D**: probability of dangerous condition (HAB)
  - P(N|D) or **P_{ND}** : probability of a negative analytical result for a dangerous condition (i.e. analysis shows no HAB, but there is a HAB)
  - P(Q|S) or **P_{QS}**: probability of a positive analytical result for a safe condition (i.e. analysis shows HAB, but there is no HAB)

Plot of C2 – C1 [$1000]
(Difference in value of decision with remote sensing and no remote sensing)



The decision model can be represented with these three variables, for example:

$$P_1 = P(Q) = (1 - P(N|D))P_D + P(Q|S)P(1 - P_D)$$
$$P_2 = P(N) = 1 - P(Q)$$
$$P_3 = P(S|Q) = \frac{P(Q|S)P(S)}{P(Q)} = \frac{P(Q|S)(1 - P_D)}{P(Q)}$$

For PD >= 0.2, decisions* can vary with level of P_{ND} and P_{Q}
Calibration will affect P_{ND} and P_{QS}

*Data for costs, and visitor traffic was based on case-study of Utah Lake provided in Stroming et al. (2020)

Value of radiometric calibration for imagery providers will depend on change in price due to data quality and market expansion

- Value of calibration for imagery providers will depend on impacts on price (due to higher data quality) and market penetration

- Calibration may increase price per area (image) by a fraction, α.

- The improved data quality may lead to increased sales by a factor β .

$$C_{calib_k} = n_L C_L + C_{sub}$$

$$R_k = n_I \alpha p + \beta n_I p(1+\alpha)$$

$$n_I \alpha p + \ \beta n_I p(1+\alpha) \geq C_{calib_k}$$

Variation in ROI with changing imagery price levels and area of imagery sold

Price after \alpha change [$/ dArea km2] \ Area sold after \beta change in sales [sq km]	2700	3375	4050	4725	5400	6075	6750	7425	8100
0	-1	-1	-1	-1	-1	-1	-1	-1	-1
460	-0.7993	-0.7491	-0.6989	-0.6487	-0.5985	-0.5484	-0.4982	-0.448	-0.3978
920	-0.5985	-0.4982	-0.3978	-0.2975	-0.1971	-0.09673	0.003636	0.104	0.2044
1380	-0.3978	-0.2473	-0.09673	0.05382	0.2044	0.3549	0.5055	0.656	0.8065
1840	-0.1971	0.003636	0.2044	0.4051	0.6058	0.8065	1.007	1.208	1.409
2300	0.003636	0.2545	0.5055	0.7564	1.007	1.258	1.509	1.76	2.011
2760	0.2044	0.5055	0.8065	1.108	1.409	1.71	2.011	2.312	2.613
3220	0.4051	0.7564	1.108	1.459	1.81	2.161	2.513	2.864	3.215
3680	0.6058	1.007	1.409	1.81	2.212	2.613	3.015	3.416	3.817
4140	0.8065	1.258	1.71	2.161	2.613	3.065	3.516	3.968	4.42
4600	1.007	1.509	2.011	2.513	3.015	3.516	4.018	4.52	5.022

Results here shown for:
Base imagery price: $23/km^2
Calibration services for 25 looks

FLARE - On-Demand, High Frequency Cal/Val Capability to enable better data and better outcomes

	Improve Quality	Validation Frequency	Saved Money	Enable Technology	Saved Hours
Calibration available on demand	X	X	X	X	X
Reduction of Image Processing Time & Human Intervention	X	X	X	X	X
Traceable & Demonstratable Performance of any Satellite Data Product (ARD)	X	X	X	X	X
A consistent & robust calibration method that is sensor agnostic	X	X	X	X	X
Fully Automated Calibration via Subscription Cloud Service		X	X		X

Summary remarks

- Value of calibration can be quantified with a conceptual 'data value chain' that models the system from data acquisition to applications and decisions

- Three different methods were shown for quantifying impact and value of calibration
  - Effective data acquired (EDA), that quantifies data quality and quantity over regions of interest over a mission lifetime, can be used for mission design and trades studies and / or for optimizing calibration station locations
  - Error analysis with analytical modeling can be used for quantifying impacts on data processing, computation of indices etc.
  - Decision analysis methods, with comparing difference in value of decisions with information (and quality of information as represented by false positive and negative error rates) can be used to quantify impact of calibration on human decisions that affect socioeconomic outcomes

References

- Stroming, et al. “Quantifying the human health benefits of using satellite information to detect cyanobacterial harmful algal blooms and manage recreational advisories in US Lakes”, GeoHealth, (2020), https://doi.org/10.1029/2020GH000254

- WHO. (1998). Guidelines for drinking water quality. Geneva: World Health Organisation

- Kasich, J., Butler, C., Zehringer, J., & Himes, L. (2016). State of Ohio Harmful Algal Bloom Response Strategy for Recreational Waters. Department of Health, Environmental Protection Agency and Department of Natural Resources.

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