After more than 15 years of research and writing, the Landsat Legacy Project Team is about to publish, in collaboration with the American Society for Photogrammetry and Remote Sensing (ASPRS), a seminal work on the nearly half-century of monitoring the Earth’s lands with Landsat. Born of technologies that evolved from the Second World War, Landsat not only pioneered global land monitoring but in the process drove innovation in digital imaging technologies and encouraged development of global imagery archives. Access to this imagery led to early breakthroughs in natural resources assessments, particularly for agriculture, forestry, and geology. The technical Landsat remote sensing revolution was not simple or straightforward. Early conflicts between civilian and defense satellite remote sensing users gave way to disagreements over whether the Landsat system should be a public service or a private enterprise. The failed attempts to privatize Landsat nearly led to its demise. Only the combined engagement of civilian and defense organizations ultimately saved this pioneer satellite land monitoring program. With the emergence of 21st century Earth system science research, the full value of the Landsat concept and its continuous 45-year global archive has been recognized and embraced. Discussion of Landsat’s future continues but its heritage will not be forgotten.

The pioneering satellite system’s vital history is captured in this notable volume on Landsat’s Enduring Legacy.

Landsat Legacy Project Team
Samuel N. Goward
Darrel L. Williams
Terry Arvidson
Laura E. P. Rocchio
James R. Irons
Carol A. Russell
Shaida S. Johnston

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ANNOUNCEMENT

Descartes Labs, a leading geospatial intelligence firm originating out of Los Alamos National Laboratory, is pleased to announce the hiring of Janie Robinson as its new Head of Government. Robinson brings more than 20 years of National Security related experience in both government and commercial capacities.

“No one is better positioned than Janie Robinson to lead our government activities as Descartes Labs expands into new roles serving the DoD and Intelligence Community (IC),” said Terry Cunningham, Descartes Labs CEO. “We have the technology to deliver actionable insights derived from any geospatial data set for U.S. commanders and warfighters anywhere in the world.”

In her position as Head of Government, Robinson is tasked with continuing to build the Descartes Labs business serving the U.S. government. Special focus will be placed on creating the right products and solutions to meet the unique needs of government organizations in every phase of their respective missions.

Robinson began her government career in a DoD cooperative education program while working towards her Bachelor of Science (BS) Electrical Engineering (EE) degree at University of North Carolina – Charlotte. She later earned a Master’s in EE at Johns Hopkins.

ACCOMPLISHMENTS

URISA is pleased to announce the newest members of its Vanguard Cabinet. The Vanguard Cabinet (VC) is a URISA initiative (which debuted in 2011) to engage young GIS practitioners, increase their numbers in the organization, and better understand the concerns facing these future leaders of the GIS community. The VC is an advisory board who represent the young membership of the organization. The Cabinet’s mission is to collaborate with URISA’s Board of Directors and Committees in creating and promoting programs and policies of benefit to young professionals.

Comprised entirely of passionate young members selected from different geospatial disciplines, the Cabinet aims to position URISA as the center of opportunities for ambitious young professionals who are committed to improving URISA and the geospatial profession via innovation, collaboration, networking, and professional development. Each will serve a three-year term.

2022-2024 URISA Vanguard Cabinet Members:

- Jordan Abbott – GIS Analyst, Cuyahoga County, Cleveland, Ohio
- Jordan Carmona – Senior GIS Analyst, Town of Prosper, Texas
- Janelle Innes - GIS/CMMS Technician, City of Delaware Department of Public Utilities, Delaware, Ohio
- Matthew Paivinen - Business Solutions Analyst (Geomatics), City of Abbotsford, British Columbia Canada
- Kendal Price – GIS Analyst, Truckee Meadows Water Authority, Reno, Nevada
- Jason Shapiro – Senior Geospatial Training Manager, Integrity Management Consulting, Washington, D.C.
- Sara Thompson - GIS Manager at IMS Infrastructure Management Services, Tempe, Arizona

Cabinet members are selected through an application process, with interviews by the URISA Leadership Development Committee. The application process for the next class of Vanguard Cabinet members will open during the Summer of 2022.

Learn more about VC activities here: https://www.urisa.org/vanguardcabinet.
GeoCue Group Inc. is pleased to announce an embedded version of Agisoft’s Metashape photogrammetric processing software. We have built interfaces directly into our LIDAR/Photogrammetric processing software, True View EVO, for driving both an embedded version of Metashape (Metashape for EVO, MfE) as well as the full GUI version of Metashape Professional. This design provides a seamless photogrammetric workflow for users of GeoCue True View EVO processing software.

While EVO has always supported generating “Photogrammetry Data Packages” for Metashape, Pix4D and Context Capture, users were still forced to exit the EVO environment to run these flows and then import results back into EVO. Now with Metashape for EVO (MfE), users can set up Metashape processing using a simple dialog and schedule the processing using EVO’s new Job Manager. The MfE job runs as a background task, allowing users to work on other projects in EVO while the MfE job runs in the background. Upon completion of the job, results are automatically added back in to the EVO project. EVO’s Job Manager can queue jobs, allowing users to set up a series of tasks to run in the background without the need to start the next job when the current one completes.

Metashape for EVO supports the generation of:

- Block Bundle Adjusted (BBA) imagery for improving the positional accuracy of imagery
- Point clouds from imagery ("structure from motion") – typically used in DJI camera workflows
- Orthomosaics

Having Metashape directly integrated into True View EVO offers some unique advantages in hybrid imagery/LIDAR workflows. These include:

- The ability to use a lidar-derived elevation model (typically a ground model) in orthomosaic generation
- For True View 3D Imaging Sensors (3DIS®), the ability to “inject” the sensor’s Applanix Position and Orientation System (POS) solution into Metashape where image correlation fails. This reduces “holes” in orthos over areas where Metashape fails to find image matches (typically over vegetation).

True View EVO with the MfE add-in supports:

- All True View 3DIS® - True View 410, 515 and 635/640 sensors
- DJI Phantom 4 RTK
- DJI M300 RTK with P1

MfE is available now and will be bundled with all new True View 515 and True View 635/640 sensors shipped after September 1, 2021. MfE is available for purchase for all other sensors. If you already own a full GUI version of Metashape Professional, True View EVO will automatically connect to and use the software. To learn more, visit www.geocue.com.

PAR Government, a provider of geospatial and decision support solutions for 50 years, today introduced GV-X™, a completely redesigned and upgraded version of its popular GV3.0™ raster imagery and full-motion video (FMV) viewing package. The new GV-X will appeal to traditional geospatial end users, especially those who perform analysis of FMV from unmanned aerial vehicles (UAVs) and other remote sensing platforms.

PAR developed the GV3.0 solution nearly 20 years ago as a government-off-the-shelf application for use exclusively by the U.S. Defense & Intelligence and GEOINT communities to view and analyze various types of raster imagery and FMV captured by satellite, drones and manned aircraft. After government support for the application ended with build 985 in 2015, PAR re-introduced GV3.0 in mid-2019 as an affordable commercial product available to all. The commercial version has updated many of the older open-source dependencies and migrated from Java 8 update 48 to the current release of Java 11 to comply with latest security requirements.

The new GV-X builds on the foundation that made the original product so popular with geospatial users. It reads many data files common in the GIS and GEOINT communities, including the National Imagiary Transmission Format (NITF) and NATO Secondary Imagiary Format (NSIF).

Enhancements to GV-X include a modernized user interface that fully leverages the 64-bit Windows10 environment and makes the software easier to access. Additionally, the underlying code has been rewritten and streamlined resulting in faster processing and functionality. Large raster files that once took minutes to load now render in seconds. For more information, visit www.pargovernment.com.

Golden Software, a developer of affordable 2D and 3D scientific modeling packages, has introduced a powerful new drillhole mapping tool that allows users to visualize in 3D the location and subsurface route of underground wells. The drillhole feature is one of several new capabilities in the latest release of Surfer that enhances the user’s ability to model, display and analyze subsurface data.

“The new drillhole functionality will be cheered by geologists, hydrologists, environmental scientists, and other Surfer users who need to analyze subsurface data associated with any type of well, borehole or drillhole,” said Kari Dickenson, Surfer Product Manager.

The Surfer package is used by more than 100,000 people worldwide, many involved in oil & gas exploration, environmental consulting, mining, engineering, and geospatial projects. Surfer enables users to model data sets, apply an array of advanced analytics tools, and graphically communicate the results in ways anyone can understand. The software has been

continued on page 794
The Analysis on the Annual Change of Digital Aerial Camera’s IMUs Boresight Misalignment
Abdullah Kayı, Bülent Bayram, and Dursun Zafer Şeker

The system calibration determines the position and orientation between the sensor and the navigation systems, such as boresight misalignment. Although there is much research about boresight calibration, there are not sufficient studies on the frequency of the calibration performance. In this study, an Ultracam Eagle digital aerial camera’s data from 2012 to 2016 were analyzed and the question of how often calibration should be performed was investigated.

Spectral Probability Distribution of Closed Connected Water and Remote Sensing Statistical Inference for Yellow Substance
Weining Zhu, Zeliang Zhang, Zaiqiao Yang, Shuna Pang, Jiang Chen, and Qian Cheng

Unlike traditional remote sensing inversion, this study proposes a new distribution–distribution scheme, which uses statistical inferences to estimate the probability distribution of in-water components based on the probability distribution of the observed spectra.

A Method of Extracting High-Accuracy Elevation Control Points from ICESat-2 Altimetry Data
Binbin Li, Huan Xie, Shijie Liu, Xiaohua Tong, Hong Tang, and Xu Wang

As a second-generation satellite, ICESat-2 is equipped with an altimeter using photon counting mode. This can further improve the application capability for stereo mapping because of the six laser beams with high along-track repetition frequency, which can provide more detailed ground contour descriptions. In this study, we propose a method using comprehensive evaluation labels that can extract high-accuracy elevation control points that meet the different level elevation accuracy requirements for large scale mapping from the ICESat-2 land-vegetation along-track product.

Diffuse Attenuation Coefficient ($K_d$) from ICESat-2 ATLAS Spaceborne Lidar Using Random-Forest Regression
Forrest Corcoran and Christopher E. Parrish

This study investigates a new method for measuring water turbidity—specifically, the diffuse attenuation coefficient of downwelling irradiance $K_d$—using data from a spaceborne, green-wavelength lidar aboard the National Aeronautics and Space Administration’s ICESat-2 satellite.

Improving Remote Sensing Multiple Classification by Data and Ensemble Selection
S. Boukie, L. Guo, and N. Chehata

In this article, margin theory is exploited to design better ensemble classifiers for remote sensing data.

Persistent Scatterer Interferometry for Pettimudi (India) Landslide Monitoring using Sentinel-1A Images
Hari Shankar, Anjot Roy, and Prakash Chauhan

The continuous monitoring of land surface movement over time is of paramount importance for assessing landslide triggering factors and mitigating landslide hazards. This research focuses on measuring horizontal and vertical surface displacement due to a devastating landslide event in the west-facing slope of the Rajamala Hills, induced by intense rainfall.
Set to the background of forested area in robust color infrared, the inset photos indicate several aspects of aerial data acquisition.

The photo on the left provides a view from beneath one of Surdex's aircraft, revealing the hole with protective glass, behind which a Leica ADS100 pushbroom image sensor is prepared to acquire imagery. This aircraft is one of our four twin turbine Cesna 441 Conquests, which is the most versatile aircraft in our fleet for acquisition of imagery over large areas.

The photo on the bottom right is from the sensor operator’s view of the cockpit, with their workstation seen on the right. During flight, the pilot is guided by carefully designed flight plans that ensure product specifications are met (e.g., imagery resolution, lidar point density). Pilots may also receive additional real-time guidance from Surdex staff on the ground who track weather and other factors influencing visibility and data quality through our FlightTracker tool. The sensor operator tracks flight progress, turbulence, and other information such as possible cloud cover using our mobile flight reporting application.

The graphic at the top is a completed flight path with a USGS 3D Elevation Program data base map. The blue dots are flown stations from a Leica DMC-I frame image sensor. These stations provide full coverage of the project areas (the hollow light blue squares). This flight mission was planned using Surdex’s Dynamic Flight Planning tool, which creates new flight plans daily for maximum acquisition efficiency.

The color infrared image in the background is a 15cm resolution aerial image acquired by Surdex in the state of Wisconsin.

As a full-service geospatial provider, Surdex manages several simultaneous aerial data projects across the country. Our Research and Development team has created a wealth of planning and tracking tools that help ensure timely, successful acquisition. Read more about them in the highlight article.

Aircraft photos and cover design by Amber Poth.

Photogrammetric Engineering & Remote Sensing is the official journal of the American Society for Photogrammetry and Remote Sensing. It is devoted to the exchange of ideas and information about the applications of photogrammetry, remote sensing, and geographic information systems. The technical activities of the Society are conducted through the following Technical Divisions: Geographic Information Systems, Photogrammetric Applications, Lidar, Primary Data Acquisition, Professional Practice, and Remote Sensing Applications. Additional information on the functioning of the Technical Divisions and the Society can be found in the Yearbook issue for PE&RS.

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Building a Comprehensive Digital Toolkit for Aerial Acquisition

Dave Beattie, CP, Aerial Triangulation Specialist
Tracy Ray, Technical Writer—Surdex Corporation
For projects involving aerial mapping, the acquisition stage must be completed in a manner that is timely, has complete coverage, and ensures all product specifications are met. With all of the challenges posed during acquisition—such as vegetation conditions, sun angle restrictions, and cloud cover, among many others—keeping acquisition on schedule is no small feat. Multiply these challenges by the number of active projects currently in the acquisition phase, and managing acquisition gets extremely tricky. Surdex’s Research & Development (R&D) department has developed several tools to ensure success in this critical project stage—starting with the planning process and continuing through acquisition flights and potential re-flights.

Creating Up-to-Date, Sensor-Specific Flight Plans
Flight plans must be carefully designed to ensure proper coverage and imagery resolution or lidar point density based on sensor specifications. Surdex creates flight plans using sensor-specific commercial software, then imports them into the Flight Manager program developed by our R&D department. This program supports the various flight plan formats generated by the commercial software and enables us to integrate flight plans into our internal database and begin tracking acquisition and inspection progress. Once lines are flown in a project area, we can update the flight plan in Flight Manager to include only remaining flight lines (or stations, for DMC imagery), then export the updated plan to the appropriate sensor-specific format for use during flight (Figures 1a and 1b).

Designing Custom Flight Plans for Dispersed Project Sites
In 2020, Surdex was awarded contracts with the USDA Natural Resources Conservation Service for two programs, the National Resources Inventory (NRI) and the Stewardship Lands Imagery (SLI) programs, which include collection of imagery for a great number of sites across the country. Since this is a departure from our usual model of large area acquisition, we wanted to customize our flight planning process to more efficiently acquire the numerous, dispersed sites.

Our R&D and Flight departments have successfully designed and implemented a unique flight planning process for these projects that includes multi-frame acquisition, adjusted flight line orientation, and collection of multiple sites per flight line. The new approach focuses on orienting flight lines for optimal collection efficiency, ensuring acquisition is completed during the scheduled window and the specified ground and atmospheric conditions.
Customized flight plans for acquisition of numerous spot shot sites include collection of multiple overlapping frames with a digital frame image sensor. The two benefits for a multi-frame approach are:

1. greater positional accuracy with a triangulated solution
2. avoiding potential re-flights due to corrupt data or glare that obstructs ground features.

Collecting overlapping frames also allows flight planning from any orientation, which greatly improves performance in flight. Rather than forcing crews to align with cardinal (N-S-E-W) directions, which often results in extra turn time, lines are oriented with multiple nearby sites, while still ensuring the pilot has a safe level of control of the aircraft (Figures 2a and 2b). The addition of extra frames on each side of the main frame(s) only adds seconds before and after the center point, resulting in insignificant additional flight time relative to traditional cardinal direction turns. This approach saves valuable time in flight and puts crews on-line sooner.

We have also designed a Dynamic Flight Planning (DFP) program, which takes all of the aforementioned flight planning customization tools for dispersed project sites and creates optimal flight plans on a daily basis. The DFP determines the shortest path to capture target sites using airport, weather and airplane performance data. This optimized flight planning reduces flight time for the entire project by at least 15%. Implementing these customized flight planning tools ensures that we can remain on schedule as we acquire imagery for thousands of sites across the country and enables us to provide clients with their data in a shorter timeframe.

Data-Rich FlightTracker Enables Informed Flight Planning

The FlightTracker online system that we created facilitates informed flight planning based on current ground and atmospheric conditions and gives staff on the ground the ability to track acquisition live. Over time, we have added several data layers and tools that have further enhanced this system. Table 1 lists many of the basic tools and features of FlightTracker. The smoke (Figure 3), fire, and spring leaf-out forecast data layers are a few of the most recent additions; all are very helpful in ensuring proper acquisition conditions. Having all of this relevant data at the fingertips of our flight and acquisition managers enables smarter acquisition, avoiding time lost attempting to acquire data in areas where conditions are not suitable for acquisition.

Table 1. FlightTracker Basic Tools

<table>
<thead>
<tr>
<th>FlightTracker Basic Tools</th>
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<tbody>
<tr>
<td>Real-time communication with the aircraft</td>
<td>High-resolution cloud cover (GOESS, NOAA)</td>
</tr>
<tr>
<td>Zoom in to a project area or view full extent of all projects</td>
<td>48-hour NOAA forecasts for specific sites</td>
</tr>
<tr>
<td>Move a time slider that allows viewing of acquisition over varying time ranges, including time-motion sequence</td>
<td>Ability to view ground condition data including snow, smoke, fires, and spring leaf-out forecast</td>
</tr>
<tr>
<td>Display time ranges for various minimum sun angle values at a specific site</td>
<td>Distance and area measuring tools</td>
</tr>
<tr>
<td></td>
<td>Ability to use different types of base maps</td>
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<tr>
<td></td>
<td>Print the current view to hardcopy, PDF, etc.</td>
</tr>
</tbody>
</table>
The ground conditions data in FlightTracker has proven particularly useful for several of Surdex’s recent aerial mapping projects. We used this tool to monitor:

- Rain/cloud cover in Illinois in late spring of 2020 for an imagery project
- Wildfires in Arizona in the summer of 2020 for a lidar project
- Flooding in North Carolina in the summer of 2020 for an imagery project
- Snow cover in late winter in Nebraska in 2021 for a lidar project

Each of the conditions noted above can obscure ground features in imagery or lidar data, sometimes to the point that data is not usable. By tracking wildfires/smoke, flooding, and snow, we were able to carefully plan acquisition times, avoiding wasted efforts during unsuitable conditions and “swarming” the area when conditions were suitable. As a specific example, for a project in western Illinois in the spring of 2020, we monitored extended periods of cloudy conditions over the project area using FlightTracker. Once conditions cleared, we sent five aircraft to acquire imagery and successfully compensated for lost time – our crews acquired 3,188 Nautical Line Miles of imagery in just one day. Figures 4a and 4b show two screen shots from FlightTracker displaying the initial flight plans with a few completed lines at the beginning of the day (Figure 4a) and the completed flight lines at the end of the day (Figure 4b) – each aircraft’s path is represented by a different colored line.
Mobile Flight Reporting Provides Detailed Flight Information to Production

The most recent flight tool to be developed is a mobile flight reporting application. This app enables sensor operators to log detailed information while a flight mission is in progress, including the specific flight lines acquired and turbulence rating as well as any potential problems with the flight, such as clouds obscuring the project area. The sensor operators log this information during the acquisition flight, then send the report to Surdex’s database when they are back on the ground and have a mobile data signal. With this flight app, acquisition managers and production personnel can review flight mission results shortly after the flight is complete (Figure 5), whereas in the past, this information was recorded in hardcopy format and sent with the acquisition data hard drives in the mail.

Having the flight report in hand sooner enables acquisition and production personnel to prepare accordingly (i.e., anticipate a large amount of project data and allocate personnel for inspection or plan re-flights if needed).

Tracking Reflights to Ensure All Data Meets Specifications

The acquisition window for a given project site can be fairly narrow; we often have just one to two weeks with the proper sun angle during leaf-off, snow-free conditions, especially in the northern United States. It is therefore important not only to complete the initial acquisition in a timely manner but also to ensure any potential re-flights are completed during the proper acquisition window. We have created a tool in our internal project database that automatically provides an updated list of re-flights every day based on the results of initial data inspection. This enables our flight crews to return to areas requiring re-flights as soon as possible, which minimizes the difference in ground conditions and overall appearance of the imagery and ensures acquisition is completed on time.

Ready for Takeoff

Acquisition is a challenging stage for every aerial mapping project. These robust flight tools make it easier for us to face this challenge and complete acquisition in a timely and efficient manner.

Authors

Dave Beattie, CP, Aerial Triangulation Specialist at Surdex Corporation, DaveB@surdex.com. Dave has a B.S. in Cartographic Sciences from Missouri State University. He has been with Surdex for 22 years, during which he has served several roles including GIS technician, sensor operator, estimator and surveyor.

Tracy Ray, Technical Writer at Surdex Corporation, TracyR@surdex.com. Tracy has a B.A. in Geography from the University of Nebraska – Lincoln and an M.A. in Geography from the University of Missouri – Columbia. She started at Surdex as an ortho technician four years ago and moved to the technical writer role after a year with the company.
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How to Play 21-Questions with your Lidar Data

As many already know, lidar (light detection and ranging) data are becoming the “go to” data source for elevation products including, terrain and surface models, hydrography, and for extracting many surface features, such as buildings and roads. As lidar sensors are constantly improving and collecting ever increasing point densities, the challenge to correctly classifying the returns is increasing. So, this month’s column offers up both a “tip” and a “challenge” to users.

In the airborne lidar industry, following acquisition and calibration, roughly 30-40% of a project’s processing budget is dedicated towards the classification of points. Using ASPRS and USGS Base Lidar Specification standards, points are generally classified into six classes including, Class 1 (Unclassified), Class 2 (bare ground), Class 7 (low noise), Class 9 (water), Class 17 (bridge deck) and Class 18 (high noise). The ASPRS vegetation classes (Class 3 – 5), the building class (Class 6) and others are generally considered for specialized applications. It should be obvious that the lidar-derivative products mentioned above are all depend on the point cloud being classified accurately.

Numerous commercial off-the-shelf (COTS) and open-source software programs are available to automate the classification process; there are even Facebook discussion groups and several YouTube channels for several of the more popular ones. Even with the large and expanding user community, after the initial automated classification, these programs require a knowledgeable analyst to manually comb through the dataset and verify the accuracy of the automated output, and to manually “clean-up” the data as needed. The automated routines are not 100% accurate. So, first the challenge... Are there alternatives to manual clean-up?

The tip... one possible alternative to manual intervention involves Artificial Intelligence/Machine Learning (AI/ML). When tackling a project with AI/ML, there are a host of methods and algorithms from which to pick. In fact, Random Trees and an implementation of UNET are available in the extended Esri ArcGIS Pro software suite. Instructions on how to install these tools can be found at: https://pro.arcgis.com/en/pro-app/2.7/help/analysis/deep-learning/install-deep-learning-frameworks.

Random Forests (decision trees), one of the “machine learning” algorithms, are predictive models that work by taking observations about data, (X, Y, Z, intensity, returns, scan angle) and then use those observations in regression models to gradually work towards a conclusion about the target variable (classification). In other words, the machine learning algorithm is playing “21 questions” with the provided information to focus in on the target.

Decision tree algorithms are preferable to other machine learning or deep learning algorithms for a few reasons, but mostly because they are not resource intensive. Many machine learning programs require powerful GPUs or process servers, while decision trees are designed to work well with CPUs in a desktop environment. For example, on a desktop CPU, these algorithms have been able to train in time frames ranging from 30 seconds to a few minutes per 5000’ x 5000’ tile with approximately 15E6 points. Classification processes in about the same time frame. Along with the speed, decision trees are fairly simple to explain, we can examine each individual classification and see how and why the algorithm came to that classification conclusion.

We have been experimenting with using various decision-tree algorithms to classify small datasets of both topographic and bathymetric lidar that were provided by NOAA and USGS (available on the NOAA Digital Coast and the US National Map). The most promising aspect of our testing so far is that the algorithms use only six parameters (X, Y and Z values, intensity data, return number vs. total number of returns, and scan angle), rather than the multiple datapoints with multiple parameters that are already used by most existing lidar classification programs. The results have been promising with classification accuracies hovering around 98%.

While there is still plenty of research to be done, from the experimenting so far, this seems like a viable solution to the manpower shortages that everyone faces and the timelines that we are always racing.

Please feel free to share your ideas and comments with us. Send your questions, comments, and tips to GISTT@ASPRS.org.

Jackson Beebe is a lidar analyst who works with all aspects of Lidar, remote sensing, photogrammetry, and GIS-related projects. As senior geospatial scientist, Al Karlin works with all aspects of Lidar, remote sensing, photogrammetry, and GIS-related projects.
Essential Biodiversity Variables (EBVs) and Earth Observation—An Invitation to Participate

ADDRESSING THE BIODIVERSITY CRISIS

Biodiversity loss and degradation, with its impacts on the sustainability of resources used by society, is developing as a major global concern for companies, government, NGOs and the public.

In response, the scientific community developed the concept of Essential Biodiversity Variables (EBVs) (Pereira et al., 2013) which provides a structure to harmonise key aspects of biodiversity from genes to landscape. EBVs are a comprehensive set of standardised observations that indicate how key aspects of biodiversity are changing over the short (1-5 years) or medium-term (10-50 years).

The definition of EBV’s encompasses six variable classes: genetic composition, species population, species traits, community composition, ecosystem structure and ecosystem function. Within each class there are a wide range of candidate EBV’s which include, for example, many well-known remote sensing products such as morphology of species, land cover, fractions of live cover, primary productivity, fire disturbance of ecosystems, phenology and species distributions (Skidmore et al. 2021). These different EBV candidates, and their associated remote sensing biodiversity products, can be observed and monitored across the range of spatial and temporal scales (Figure 1).

THE ROLE OF EARTH OBSERVATION

Earth Observation data offer insights into both the spatial and temporal patterns of many EBV’s as well as their change in time and space using a range of platforms including satellite systems, aircraft and remote piloted systems as well as terrestrial sensors. The role of spatial sciences in general, and remote sensing in particular, are key elements in many of the EBV’s as most biodiversity observations are collected in the field by in situ observations based at a point in time. With remote sensing we can interpolate and model in space and time many key biodiversity variables. A recent paper details and prioritizes the 30 top biodiversity remote sensing products which can be retrieved now or in the next decade from remote sensing (Skidmore et al., 2021). They conclude current and emerging next-generation satellite remote sensing technologies are an ideal tool for the continuous detection of changes in biodiversity from local to global levels, thereby filling data gaps in the spatial and temporal coverage of in situ observations.

When observed from spacecraft, specific EBV’s can be monitored at near global scales, thereby providing significant benefit to the biodiversity community through remote sensing biodiversity products that can be integrated into global, national and regional biodiversity monitoring programs. A number of key technologies with unique capacity to predict some EBV’s are only able to be flown (currently) on aircraft systems, for example small footprint lidar and hyperspectral data. In these cases, data sets are more limited in spatial coverage, and temporal resolution, and whilst these data sets still have critical roles to play in biodiversity monitoring programs, they are more likely to be relevant at local and regional levels, rather than in a global context.

Since the definition of the EBV concept over a decade ago there has been research and documentation on which of these EBV’s are best suited to observation by remote sensing technologies. This attention has focused on how to best apply Earth Observation technologies (for example proof of concepts and best practice guides). More recently there has been a push towards working more collaboratively with space agencies to develop new sensor technologies such as image spectroscopy as well as LiDAR that are able to provide insights into EBVs currently not well detected using existing technologies. The availability of space-based LiDAR lidar and image processing systems designed for vegetation structure and ecosystem function (e.g., stress) are providing near global estimates of attributes likely to be highly relevant to the estimation and monitoring of biodiversity.

INVITATION TO CONTRIBUTE

A key organisation for biodiversity monitoring is the UN Group on Earth Observation Biodiversity Observation Network or GEOBON. GEOBON is a global network of hundreds of biodiversity scientists, users, companies and governments,
and has been examining through a working group structure each of the EBV classes, producing a number of peer reviewed papers on each EBV class. In addition, GEOBON has overseen the establishment of a number of biodiversity observation networks at the national and international level as well as across biomes for example SOILBON and MARINEBON. Each working group has been tasked with examining each EBV class to focus on which EBVs are the most suitable for measurement, detection, and sensitive to change. They are working closely with taskforces focused on data management and remote sensing to ensure that the proposed observation networks can be applied across time and space. Remote Sensing is a key area of science filling the gaps between field based biological observations and allowing upscaling from local to global levels.

As the EBV concept matures, so too will the approaches of GEOBON to developing future observation networks and metrics for biodiversity as well as informing the most applicable use of remote sensing technologies for biodiversity assessment. GEOBON has strong links to National Aeronautics and Space Administration (NASA), European Space Agency (ESA) and Committee on Earth Observation Satellites (CEOS), and is active in key biodiversity networks including the UN Convention on Biodiversity as well as the Biodiversity and Ecosystem Services (IPBES) Satellites.

As we move forward in the continuing development and demonstration of EBV’s, key directions will focus on exploration of how to bridge the work of ecologists (who address the efficacy of using EBVs for biodiversity monitoring) and remote sensing specialists (who address technologies deriving remote sensing products related to EBVs). In particular a focus of discussion includes the technical requirements needed to ensure that EBVs are operationally realistic from a remote sensing perspective. We need your help and welcome your involvement in the GEOBON Remote Sensing activities. To do so, please reach out to the co-authors.

**Authors**

**Professor Nicholas Coops**, nicholas.coops@ubc.ca, is based at the University of British Columbia and is a Canada Research Chair in remote sensing. He researches the application of remote sensing technologies to forestry; with focus on forest production and conservation issues. He is currently the Remote Sensing Task Force co-Lead for Group on Earth Observation Biodiversity Observation Network (GEOBON), with Professor Skidmore. Department of Forest Resource Management, 2424 Main Mall, University of British Columbia, Vancouver, British Columbia, Canada V6T 1Z4.

**Professor Andrew Skidmore**, a.k.skidmore@utwente.nl, is on the faculty of Geo-Information Science and Earth Observation (ITC), University of Twente. He uses remote sensing to monitor plant and animal life across the world. His research focuses on tools for image processing, terrain modelling and machine learning. After working in forest management for a decade, Skidmore worked at the University of New South Wales, and at the ITC Faculty of the University Twente, the Netherlands. He is currently the Remote Sensing Task Force co-Lead for Group on Earth Observation Biodiversity Observation Network (GEOBON), the Mission Advisory Group for the European Space Agency hyperspectral CHIME satellite, and technical committee member for the IGARSS 2021 conference. Geo-Information Science and Earth Observation (ITC), University of Twente, P.O. Box 217, 7500, AE Enschede, the Netherlands.

Virtual Surveyor has developed an enhanced point cloud workflow for Version 8.3 of its drone surveying software that allows users to take full advantage of the new lidar payloads like the DJI Zenmuse L1. LiDAR drone sensor systems enable users to capture survey-grade elevation data even in vegetated terrain.

Virtual Surveyor is a robust surveying software that bridges the gap between drone photogrammetric processing applications and engineering design packages, enabling surveyors to derive topographic information from drone data needed by engineers for construction, mining, and excavation projects. The software presents an interactive onscreen environment with drone orthophotos, digital surface models (DSMs), and/or lidar point clouds where users generate CAD models, create cut-and-fill maps, and calculate volume reports.

Current subscribers to Virtual Surveyor will see their software updated to Version 8.3 automatically. To start a free 14-day trial of Virtual Surveyor and to view details of the three pricing plans, visit www.virtual-surveyor.com.
The Grids & Datums column has completed an exploration of every country on the Earth. For those who did not get to enjoy this world tour the first time, PE&RS is reprinting prior articles from the column. This month’s article on the Commonwealth of Australia was originally printed in 2003 but contains updates to their coordinate system since then.

Originally populated by aborigines who probably came from Asia about 40,000 years ago, Australia was first sighted by the Spanish in the early 17th century. In 1606, the Dutch landed on the eastern coast of the Bay of Carpentaria and named it New Holland. The eastern part was claimed by Capt. James Cook in 1770 and named New South Wales. The first English settlement at Port Jackson was mainly populated by convicts and seamen in 1788.

Capt. Matthew Flinders circumnavigated Australia from 1801-1803 and exhibited a level of professionalism not previously seen in the hydrographic charting expeditions of others in the British Admiralty, such as Vancouver. Capt. Flinders received his initial instruction in navigation and chart making as well as tongue-lashings by Capt. William Bligh of the Bounty during the successful breadfruit voyage from Tahiti to the Caribbean. It was on that early voyage that Capt. Flinders was in charge of the navigation chronometers. (*The Admiralty Chart* by RADM G. S. Ritchie, 1995.)

Capt. Flinders proved the continental unity of New Holland and New South Wales. Named Australia in the 19th century, the entire continent was claimed by the United Kingdom (*PE&RS*, October 2003) in 1829. The continent of Australia is slightly smaller than the United States; the lowest point is Lake Eyre (–15 m), and the highest point is Mount Kosciusko (2,229 m). The *CIA Factbook* describes the country as mostly low plateau with deserts; fertile plain in southeast and having a generally arid to semiarid climate that is temperate in the south and east; tropical in the north. A further note points out that Australia is the “world’s smallest continent but sixth-largest country; population concentrated along the eastern and southeastern coasts; regular, tropical, invigorating, sea breeze known as ‘the Doctor’ occurs along the west coast in the summer.”

The first astronomical “fix” or precise position determination along the coast of southern Australia was by Capt. Flinders in 1801 when he wrote: “The latitude of our tents at the head of Port Lincoln, from the mean of four meridian observations of the Sun taken from an artificial horizon was 34° 48’ 25” S. The longitude from thirty sets of distances of the sun (sic) and stars from the moon was 135° 44’ 51” E. – (Ritchie, 1995). The enormous size of the country and the fact that this continent is surrounded by water has resulted in many local datums being established in coastal areas and little early geodetic work in the vast interior. Among those lesser datums known to exist on the Clarke 1858 ellipsoid are: Adelaide Observatory, Astro Fixation Western Australia 21, Army OP LA22 Lacrosse Island, Valentine, Australian Pillar, Central Origin 1963, Cooke’s Pillar Broome, Townsville, Emery Point Lighthouse, Final Sidney 1941, Gladstone Observatory Spot, Old Sydney, Maurice 1962, Melbourne Observatory, Weipa Mission Astro, Mildura Aerodrome, Mt. Rapid Fleurien Peninsula, Plantation Point.
Prior to the Australian Geodetic Datum of 1966, the Clarke 1858 ellipsoid as used in Tasmania was \( a = 6,378,293.645 \) meters and \( 1/f = 294.26 \) and in Australia proper was \( a = 6,378,339.78 \) meters and \( 1/f = 294.26 \). The difference between the two was the Clarke foot = 0.3047972654 meters versus the British foot of 1926 = 0.30479947 meters. Of the earlier more important datum origins, there were: Sydney Observatory where: \( \Phi_0 = 33° 51’ 41.10” \) S and \( \Lambda_0 = 151° 12’ 17.85” \) E, Perth Observatory 1899 where: \( \Phi_0 = 31° 57’ 09.63” \) S and \( \Lambda_0 = 115° 50’ 26.10” \) E, Darwin Origin Pillar where: \( \Phi_0 = 12° 28’ 08.452” \) S and \( \Lambda_0 = 130° 50’ 19.802” \) E, and Lochmaben Astro Station in Tasmania where: \( \Phi_0 = 41° 38’ 23.389” \) S and \( \Lambda_0 = 147° 17’ 49.725” \) E. The astronomical longitudes differed from geodetic longitudes on either the Sidney or Perth origins on an average of 10”, which indicated the magnitude of the deflections of the vertical.

During the 1930s, the Australia Belts were devised on the Transverse Mercator projection. Referenced to the Clarke 1858 ellipsoid, and an ersatz military datum, the scale factor was equal to unity; the belts were numbered from 1 to 8 and were 5° wide, starting with a central meridian at 116° and continuing east. Each belt had a false Easting at the central meridian of 400,000 yards, and the False Northing origin was 800,000 yards at 34° S. A caveat published by the U.S. Lake Survey, New York Office in 1944 cautioned: “If these false coordinates are used, negative values will result in false positions. This adjustment produced a set of coordinates which, in the form of latitudes and longitudes, was known as the Australian Geodetic Datum 1966 coordinate set (AGD66). The grid coordinates derived from a Universal Transverse Mercator projection of the AGD66 coordinates, used the Australian National Spheroid, and was known as the Australian Map Grid 1966 coordinate set (AMG66). New South Wales instituted the Integrated Survey Grid (ISG) where the projection was the Transverse Mercator truncated to the cubic terms since the belts were only 2° wide with a ½“ overlap. The scale factor at origin, mo = 0.99994, the False Easting (FE) = 300 km and the False Northing (FN) = 5,000 km at the equator. The central meridians \( \lambda_0 = 141°, 143°, \) etc. to 153° E.

Thanks to Geomatics Australia, “While much early mapping was based on these origins, some 1:250,000 maps were based only on astronomical observations with an accuracy of the order of 100 metres or more, or by a mixture of astro and conventional surveying. A comparison of coordinates based on different origins of this kind will include differences due to the uncertainty of the astronomical observation as well as the deflections of the vertical and could show differences of several hundreds of metres.

For a short period in 1962, geodetic computations were performed on the so-called ‘NASA’ spheroid with an origin at Maurice as below; but these computations were completely superseded.” \( a = 6,378,148 \) m, \( 1/f = 298.3 \). “From the end of 1962 until April 1965, the computation and adjustment of the Australian Geodetic Survey was done on the ‘165’ spheroid: \( a = 6,378,165 \) m, \( 1/f = 298.3 \). Prior to April 1963, the ‘Maurice’ origin used with the NASA spheroid was retained. As a result of these computations, new origin values were determined and from April 1963 to April 1965, computations were made on the 165 spheroid and this new ‘Central’ origin. Computations still emanated from Maurice whose various coordinates were: 165 Central: S 32° 51’ 13.979”, E 138° 30’ 34.062”, 165 Maurice: S 32° 51’ 13.000”, E 138° 30’ 34.000”, Clarke 1858, Sydney: S 32° 51’ 11.482”, E 138° 30’ 42.29”, and Astronomic: S 32° 51’ 11.341”, E 138° 30’ 25.110”. The Central origin was based on the best mean fit to 155 Laplace stations spread over the whole of Australia with the exception of Cape York and Tasmania. The residual mean deflection was less than 0.1” in both latitude and longitude whether isostatic topographic corrections were applied to the astronomic values or not. It was therefore considered unlikely that there was a significant artificial component in N with the Central origin. As no observed values of N from geoid surveys existed, it was assumed that N is everywhere zero. (N” here refers to the separation between the geoid and the ellipsoid – Ed.)

“In April 1965, it was changed to the spheroid adopted by the International Astronomical Union and this spheroid was called the Australian National Spheroid: \( a = 6,378,160 \) m, and \( 1/f = 298.25 \). In May 1965 a complete recomputation of the geodetic surveys of Australia was begun, emanating from the trigonometrical station Grundy, whose coordinates on both the 165, Central datum and the Australian National Spheroid, Central origin were: S 25° 54’ 11.078”, E 134° 32’ 46.457”. By December 1965, the total number of Laplace stations in Australia was 533. From these, 275 stations were selected ... no corrections for the topography were applied ... and it was found that random undulations in the geoid make it impossible to locate a centre for the spheroid with a standard error of less than 0.5 seconds, about 15 metres, even with a very large number of stations.

“The Central origin was therefore retained, but is now defined in terms of the Johnston memorial cairn. The Central origin was originally defined in terms of the trigonometrical station Grundy. The spheroid is oriented by defining the photographic zenith tube at Mt. Stromlo. The size, shape, and orientation of the spheroid are thus completely defined, and together define the Australian Geodetic Datum:
Johnston S 25° 56’ 54.5515˝, E 133° 12’ 30.0771˝, h = 571.2 meters ellipsoid height.

“The Geocentric Datum of Australia 1994 (GDA94) is the new Australian coordinate system, replacing the Australian Geodetic Datum (AGD). GDA is part of a global coordinate reference frame and is directly compatible with the Global Positioning System (GPS). It is the culmination of more than a decade of anticipation and work by the Intergovernmental Committee on Surveying and Mapping (ICSM) and its predecessor, the National Mapping Council (NMC). When the NMC adopted the AGD84 coordinate set in 1984, it ‘recognised the need for Australia to eventually adopt a geocentric datum.’ This was further recognised in 1988 when ICSM ‘recommen...d the adoption of an appropriate geocentric datum by 1 January 2000.’

The state of Western Australia has the “Project Grids” that closely correspond to what we use in the United States as State Plane Coordinates. The new Project Grids for the GDA94 Datum as well as for the previous datum for each are used for the following regional areas: Albany GDA94 – \( \lambda_0 = 117° 53’ 00˝, m_o = 1.00000440, FE = 50 km, FN = 4,000 km, \) and for Albany AGD84 – \( \lambda_0 = 117° 55’ 00˝, m_o = 1.00000550, FE = 50 km, FN = 4,000 km; for Broome GDA94 – \( \lambda_0 = 122° 20’ 00˝, m_o = 1.00000298, FE = 50 km, FN = 2,200 km, \) and for Broome AGD84 – \( \lambda_0 = 122° 20’ 00˝, m_o = 1.00000003, FE = 50 km, FN = 2,200 km; Busselton GDA94 – \( \lambda_0 = 115° 26’ 00˝, m_o = 0.999999592, FE = 50 km, FN = 3,900 km, \) and for Busselton AGD84 – \( \lambda_0 = 115° 26’ 00˝, m_o = 1.0000007, FE = 50 km, FN = 3,900 km; for Carnarvon GDA94 – \( \lambda_0 = 113° 40’ 00˝, m_o = 0.99999796, FE = 50 km, FN = 2,950 km, \) and for Carnarvon AGD84 – \( \lambda_0 = 113° 40’ 00˝, m_o = 1.00000005, FE = 50 km, FN = 3,050 km; for Christmas Island GDA94 – \( \lambda_0 = 105° 37’ 30˝, m_o = 1.000002514, FE = 50 km, FN = 1,300 km, \) and for Christmas Island WGS84 – \( \lambda_0 = 105° 37’ 30˝, m_o = 1.0000024, FE = 50 km, FN = 1,300; for the Cocos (Keeling) Islands AGD94 – \( \lambda_0 = 96° 52’ 30˝, m_o = 0.999999387, FE = 50 km, FN = 1,500 km, \) and for the Cocos (Keeling) Islands WGS84 – \( \lambda_0 = 96° 52’ 30˝, m_o = 1.0, FE = 50 km, FN = 1,400 km; for Collie GDA94 – \( \lambda_0 = 115° 56’ 00˝, m_o = 1.0000190, FE = 40 km, FN = 4,000 km; for Esperance GDA94 – \( \lambda_0 = 121° 53’ 00˝, m_o = 1.00000550, FE = 50 km, FN = 3,950 km, \) and for Esperance AGD84 – \( \lambda_0 = 121° 53’ 00˝, m_o = 1.00000012, FE = 50 km, FN = 3,950 km; for Exmouth GDA94 – \( \lambda_0 = 114° 04’ 00˝, m_o = 1.00000236, FE = 50 km, FN = 2,650 km, \) and for Exmouth AGD84 – \( \lambda_0 = 114° 04’ 00˝, m_o = 1.0000009, FE = 50 km, FN = 2,750 km; for Geraldton GDA94 – \( \lambda_0 = 114° 35’ 00˝, m_o = 1.00000628, FE = 50 km, FN = 3,350 km, \) and for Geraldton AGD84 – \( \lambda_0 = 114° 40’ 00˝, m_o = 1.00000016, FE = 50 km, FN = 3,350 km; for Goldfields GDA94 – \( \lambda_0 = 121° 30’ 00˝, m_o = 1.000004949, FE = 60 km, FN = 3,700 km, \) and for Goldfields AGD84 – \( \lambda_0 = 121° 27’ 00˝, m_o = 1.000057, FE = 60 km, FN = 4,000 km; for Jurien GDA94 – \( \lambda_0 = 114° 59’ 00˝, m_o = 1.0000314, FE = 50 km, FN = 3,550 km, \) and for Jurien AGD84 – \( \lambda_0 = 114° 59’ 00˝, m_o = 1.0000001, FE = 50 km, FN = 3,550 km; for Karratha GDA94 – \( \lambda_0 = 116° 56’ 00˝, m_o = 0.99999890, FE = 50 km, FN = 2,450 km, \) and for Karratha AGD84 – \( \lambda_0 = 116° 56’ 00˝, m_o = 1.0000004, FE = 50 km, FN = 2,450 km; for Kununurra GDA94 – \( \lambda_0 = 128° 45’ 00˝, m_o = 1.00001650, FE = 50 km, FN = 2,000 km, \) and for Kununurra AGD84 – \( \lambda_0 = 128° 45’ 00˝, m_o = 1.00000114, FE = 50 km, FN = 2,000 km; for Lancelin GDA94 – \( \lambda_0 = 115° 22’ 00˝, m_o = 1.00000157, FE = 50 km, FN = 3,650 km, \) and for Lancelin AGD84 – \( \lambda_0 = 115° 22’ 00˝, m_o = 1.000000157, FE = 50 km, \) and for Margaret River GDA94 – \( \lambda_0 = 115° 10’ 00˝, m_o = 0.99999960, FE = 50 km, FN = 3,800 km, \) and for Margaret River AGD84 – \( \lambda_0 = 115° 10’ 00˝, m_o = 0.99999960, FE = 50 km, FN = 3,800 km; for Perth GDA94 – \( \lambda_0 = 115° 49’ 00˝, m_o = 1.00000006, FE = 40 km, FN = 3,800 km; for Port Hedland GDA94 – \( \lambda_0 = 118° 36’ 00˝, m_o = 1.00000135, FE = 50 km, FN = 2,400 km, \) and for Port Hedland AGD84 – \( \lambda_0 = 118° 35’ 00˝, m_o = 1.0000004, FE = 50 km, FN = 2,400 km.

Datum shifts between the various classical datums and the various scientific reference frames of the GPS satellites are available for cartographic-accuracy transformations. However, for precise geodetic applications, the parameters change monthly because the entire continent is moving to the Northeast at about 3 centimeters per year! For instance, a couple of cartographic transform accuracy parameter sets are given as follows: From Australian Geodetic Datum 1966 (Victoria/New South Wales) to WGS84: \( \Delta X = –119.353 m, \Delta Y = –48.301 m, \Delta Z = +139.844 m, R_x = –7.243 \times 10^{-3} \) radians, \( R_y = –4.538 \times 10^{-3} \) radians, \( R_z = –7.627 \times 10^{-3} \) radians, and \( \Delta s = –6.13 \times 10^{-1} \). From Australian Geodetic Datum 1984 to WGS84: \( \Delta X = –117.763 m, \Delta Y = –51.54 m, \Delta Z = +139.061 m, R_x = –5.096 \times 10^{-3} \) radians, \( R_y = –4.835 \times 10^{-3} \) radians, \( R_z = –7.732 \times 10^{-3} \) radians, and \( \Delta s = –1.91 \times 10^{-1} \). Australia is a free and open society. Their geodesy is not a secret and their history, their coordinates, and their datum transformations are an open book – a very large open book, but definitely open. Thanks go to Malcolm A. B. Jones, “Geodesy Jones,” of the Louisiana State University Center for GeoInformatics (C3G).

The contents of this column reflect the views of the author, who is responsible for the facts and accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the American Society for Photogrammetry and Remote Sensing and/or the Louisiana State University Center for GeoInformatics (C3G).

This column was previously published in PEERS.
**AI-Based Environmental Monitoring with UAV Systems**

*Photogrammetric Engineering and Remote Sensing (PE&RS)* is seeking submissions for a special issue on AI-Based Environmental Monitoring with UAV Systems.

Global warming and climate change have become the most important factor threatening the world. Climate change results in dramatic environmental hazards and threatens the planet and human life. A wide variety of policies have been proposed to decrease the effects of global warming and climate change. The most important one is the Paris Agreement which aims to limit global warming to well below two degrees Celsius. Many countries have formulated long term low greenhouse gas emission development strategies related to the Paris Agreement which aimed to meet the essential strategies addressing issues with climate change, environmental protection and low carbon.

The astonishing developments on unmanned aerial vehicle (UAV) systems and artificial intelligence (AI) technologies enables a great opportunity to monitor the environment and propose reliable solutions to restore and preserve the planet and human health.

Data acquisition and processing paradigm has been changed as a result of technological developments. It is obvious that new solutions, innovative approaches will make significant contributions to solve the problems which our planet is facing. UAV data can be collected by various platforms (planes or helicopters, fixed wing systems, drones) and sensors for earth observation and sustainable environmental monitoring which are also utilized by the United Nations to support the delivery of its mandates, resolutions, and activities.

UAV based earth observation data and AI techniques have a wide range of applications such as risk management, disaster monitoring and assessment, environmental impact evaluation and restoration, monitoring agriculture and food cycles, urban analysis, digital twin and smart city applications and providing increased situation awareness. This growth of widely available UAV data associated with the exponential increase in digital computing power, machine learning and artificial intelligence plays a key role in the environmental monitoring and solution generation of geospatial information for the benefit of humans and the planet.

The proposed special issue aims to contributes ASPRS’s key mission on ‘Simplify and promote the use of image-based geospatial technologies for the end-user’, ‘Promote collaboration between end users and geospatial experts to match data and technology to applications and solutions’ and ‘promote the transfer of geospatial data and information technology to developing nations’ by serving as an innovative knowledge exchange platform for authors from the globe to deliberate on the latest advancements, state-of-the-art developments and solutions that can help the community to solve many real-world challenges on the topic of “AI-Based Environmental Monitoring with UAV Systems.”

This special issue aims to bring researchers to share knowledge and their expertise about state-of-art developments and contribute to the goal of a livable world by integrating human creativity with UAV and AI technologies for environmental monitoring to combat global threats on ecosystems. We wish to discuss the latest developments, opportunities and challenges that can solve many real-world challenges in environmental monitoring including but not limited to:

- AI-Based UAV and GIS Applications
- AI-Based Object Detection and Recognition from UAV Imagery
- AI-Based Digital Twin Applications
- AI-Based Smart City Applications

Papers must be original contributions, not previously published or submitted to other journals. Submissions based on previous published or submitted conference papers may be considered provided they are considerably improved and extended. Papers must follow the instructions for authors at [http://asprs-pers.edmgr.com/](http://asprs-pers.edmgr.com/).

**Deadline for Manuscript Submission**

May 1, 2022

Submit your Manuscript to [http://asprs-pers.edmgr.com](http://asprs-pers.edmgr.com)

**Guest Editor**

Tolga Bakirman, PhD, Yildiz Technical University, Turkey

Dr. Tolga Bakirman. bakirman@yildiz.edu.tr. is an assistant professor at Yildiz Technical University in the Department of Geomatic Engineering.
ASPRS’S NEW DIVERSITY, EQUITY, AND INCLUSION (DEI) COMMITTEE

ASPRS is pleased to announce the formation of a new Diversity, Equity, and Inclusion (DEI) Committee, building from the efforts of the Diversity Taskforce over the past year. ASPRS values diversity as a strength of the geospatial professions and seeks to promote a culture of equity and inclusion. The DEI Committee is currently meeting every other Monday at 4pm Eastern.

Everyone is welcome, and we are currently seeking new, active participants. Please contact diversity@asprs.org to get involved!

NEW ASPRS MEMBERS

ASPRS would like to welcome the following new members!

Joseph E. Ambroigne
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Schyler Brennan Brown
Michael Calvelli
Rob Davis, PLS
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The Analysis on the Annual Change of Digital Aerial Camera’s IMUs Boresight Misalignment

Abdullah Kayı, Bülent Bayram, and Dursun Zafer Şeker

Abstract

The system calibration determines the position and orientation between the sensor and the navigation systems, such as boresight misalignment. Although there is much research about boresight calibration, there are not sufficient studies on the frequency of the calibration performance. The short-term stability of boresight misalignment was investigated in previous studies, but long-term stability research could not be done. It is important to emphasize that long-term stability is still open to questions. In this study, an Ultracam Eagle digital aerial camera’s data from 2012 to 2016 were analyzed and the question of how often calibration should be performed was investigated. Boresight misalignment does not remain constant on a yearly basis and should be calibrated every year before the flight season. It was observed that the boresight misalignment changed dramatically when the inertial measurement unit or camera was removed from the aircraft and sent to the manufacturer for factory calibration.

Introduction

In the early 2000s, digital aerial cameras increasingly replaced analog aerial cameras in the field of airborne imaging. With the developments in global navigation satellite system/inertial measurement unit (GNSS/IMU) integration systems and the widespread use of digital aerial cameras, photogrammetric data acquisition sensitivity has increased. The determination of exterior orientation parameters during data acquisition became possible through integrated GNSS/IMU systems. The accuracy of the external orientation parameters is related to the precision of the sensors and synchronization of the systems. However, the complex structure of digital aerial cameras and the integration of the GNSS/IMU system have further complicated the calibration process.

Calibration refers to checking the accuracy of another test or instrument through using a known standard or system under a particular condition. Calibration is a refined measurement process in which not only the accuracy of measurements is checked but also the accuracy of the results is increased; this ultimately warrants that the measurements are accurate and systematic (Eisenhart 1963). Giri (2016) defined the calibration as “...the process of quantitatively defining a system’s response to known controlled signal inputs. The system parameters are obtained from well-defined conditions...”. Individual sensor calibration, such as a camera’s interior orientation parameters, is usually carried out by the manufacturer while the calibration between sensors, such as lever arm, are conducted by the users (Geenens et al. 2015).

When the definitions of calibration by Eisenhart and Giri are adapted to the photogrammetric data collection workflow, it becomes evident that the imaging sensors, components, and navigation systems should be calibrated separately and together. The overall system accuracy is mainly dependent on the high precision system calibration (Cramer et al. 2001). The system calibration is divided into two parts: calibration of individual sensors for precision and calibration between sensors for synchronization (Skaloud 1999).

User calibration is the determination of the position and orientation between the sensor and the navigation systems. That is, the spatial relationship among the IMU, GNSS antenna, and the camera is modeled. The first component of the system calibration is the measurement of the lever-arm. The GNSS antenna is mounted on the upper fuselage and the camera is mounted on the underside of the fuselage. The spatial shift between the GNSS antenna and the camera perspective center is called the lever-arm (Cramer and Stallmann 2001). The lever-arm should be roughly measured by a ground survey technique and precisely determined with a Kalman filter while using GNSS/IMU for data processing (Cramer et al. 2000; Skaloud 2006) The second component is the calculation of boresight misalignment, which is expressed as the misalignment between the IMU body frame with respect to the imaging sensor frame (Mostafa 2001; Yastikli et al. 2007). IMU is a navigation sensor including an accelerometer, gyroscope, and magnetometer which collect data based on the movement of the aircraft. The IMU body frame where the inertial data are resolved is the coordinate frame of the IMU. The imaging sensor frame is an image position frame which is used for the calculation of exterior orientation parameters (Manon 2017).

Since these two axes would not be parallel to each other, the difference must be determined. Unlike the lever-arm measurement, it is not possible to directly measure the boresight misalignment because the sensor axis in both devices cannot be physically observed (Haala et al. 1998). Due to physical constraints, boresight misalignment is determined by special calibration flights by an in situ calibration method (Honkavaara et al. 2006). The basic assumption of the calibration flight is based on the fact that the relative position between the IMU and the camera remains constant at the time of flight (Skaloud et al. 1996). Therefore, it is necessary to ensure that the imaging sensor and IMU are mounted tightly together on the aircraft (Hutton and Mostafa 2005).

The debate on the stability of the boresight misalignment started after the definition and determination process of boresight calibration. The analysis of the stability of boresight misalignment was investigated in two stages. Studies...
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Spectral Probability Distribution of Closed Connected Water and Remote Sensing Statistical Inference for Yellow Substance

Weining Zhu, Zeliang Zhang, Zaiqiao Yang, Shuna Pang, Jiang Chen, Qian Cheng

Abstract
Unlike traditional remote sensing inversion, this study proposes a new distribution–distribution scheme, which uses statistical inferences to estimate the probability distribution of in-water components based on the probability distribution of the observed spectra. The distribution–distribution scheme has the advantages that it rapidly gives the statistical information of the water of interest, assists the traditional scheme in improving models, and provides more valuable information for water classification and aquatic environment analysis. In this study, based on Landsat-8 images, we analyzed the spectral probability distributions of 688 global lakes and found that many of them were normal, log normal, and exponential distributions with diverse patterns in distribution parameters such as the mean, standard deviation, skewness, and kurtosis. Using simulated and field-measured data, we propose a bootstrap-based distribution–distribution scheme and develop some simple remote sensing statistical inference models to estimate the distribution parameters of yellow substance in water.

Introduction
An important content of aquatic remote sensing is estimating the properties of in-water components from the above-surface spectra (Bukata et al. 1995; O’Reilly et al. 1998). In Figure 1a, the absorption coefficient of yellow substance (also called colored dissolved organic matter [CDOM]) at 440 nm—i.e., aCDOM(440)—was estimated from the spectrum at an image pixel in the lake of interest (Kutser et al. 2005; Zhu et al. 2014; Chen et al. 2017; Li et al. 2017) using a remote sensing inversion model—we call this approach the spectrum–concentration (SC) scheme of ocean color remote sensing. In this study we propose a new research scheme, which we call a distribution–distribution (DD) scheme, using statistical inference to estimate the statistical distribution of CDOM in an entire lake based on the spectral probability distributions (SPDs) of all water pixels over the lake at different wavelengths (Figure 1b). The SPD can be defined as the statistical distribution of the observed reflectance in a region of interest (ROI) in an image. For example, an ROI consists of N image pixels; at pixel k, with a reflectance of \( R = 0.3 \), the probability \( P(R=0.3) = k/N \). Typically, SPD is presented by the spectral frequency histogram, which can be easily calculated by many well-known remote sensing programs, such as ENVI and ERDAS. More statistically, the spectral histogram can be described by a probability distribution function (pdf), such as a normal or exponential distribution. Note that the SPD is different from the spatial distribution. We can obtain the SPD from the spatial distribution of the remotely sensed reflectance, but inversely, the SPD does not provide any spatial information of the observed spectra.

Weining Zhu is with the Key Laboratory of Ocean Observation-Imaging Testbed of Zhejiang Province, Ocean College, Zhejiang University, Zhejiang, China; and the Department of Marine Information Science, Ocean College, Zhejiang University, Zhejiang, China (zhuwn@zju.edu.cn).
Zaiqiao Yang is with the Department of Marine Information Science, Ocean College, Zhejiang University, Zhejiang, China.
Zeliang Zhang and Shuna Pang are with the Department of Marine Science, Ocean College, Zhejiang University, Zhejiang, China.
Jiang Chen is with the School of Remote Sensing and Information Engineering, Wuhan University, Hubei, China.
Qian Cheng is with the School of Tourism and Urban-Rural Planning, Zhejiang Gongshang University, Zhejiang, China.

Contributed by Desheng Liu, December 16, 2020 (sent for review April 30, 2021; reviewed by Liqiao Tian, Qian Yu).
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The 3rd edition of the DEM Users Manual includes 15 chapters and three appendices. References in the eBook version are hyperlinked. Chapter and appendix titles include:

1. Introduction to DEMs  
   David F. Maune, Hans Karl Heidemann, Stephen M. Kopp, and Clayton A. Crawford
2. Vertical Datums  
   Dru Smith
3. Standards, Guidelines & Specifications  
   David F. Maune
4. The National Elevation Dataset (NED)  
   Dean B. Gesch, Gayla A. Evans, Michael J. Omoen, and Samantha T. Arundel
5. The 3D Elevation Program (3DEP)  
   Jason M. Stoker, Vicki Lukas, Allyson L. Jason, Diane F. Eldridge, and Larry J. Sugarbaker
6. Photogrammetry  
   J. Chris McGlone and Scott Arko
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13. DEM User Applications  
    David F. Maune
14. DEM User Requirements & Benefits  
    David F. Maune
15. Quality Assessment of Elevation Data  
    Jennifer Novac
    Appendix A. Acronyms
    Appendix B. Definitions
    Appendix C. Sample Datasets

This book is your guide to 3D elevation technologies, products and applications. It will guide you through the inception and implementation of the U.S. Geological Survey’s (USGS) 3D Elevation Program (3DEP) to provide not just bare earth DEMs, but a full suite of 3D elevation products using Quality Levels (QLs) that are standardized and consistent across the U.S. and territories. The 3DEP is based on the National Enhanced Elevation Assessment (NEEA) which evaluated 602 different mission-critical requirements for and benefits from enhanced elevation data of various QLs for 34 Federal agencies, all 50 states (with local and Tribal input), and 13 non-governmental organizations.

The NEEA documented the highest Return on Investment from QL2 lidar for the conterminous states, Hawaii and U.S. territories, and QL5 IfSAR for Alaska.

Chapters 3, 5, 8, 9, 13, 14, and 15 are “must-read” chapters for users and providers of topographic lidar data. Chapter 8 addresses linear mode, single photon and Geiger mode lidar technologies, and Chapter 10 addresses the latest in topobathymetric lidar. The remaining chapters are either relevant to all DEM technologies or address alternative technologies including photogrammetry, IfSAR, and sonar.

As demonstrated by the figures selected for the front cover of this manual, readers will recognize the editors’ vision for the future – a 3D Nation that seamlessly merges topographic and bathymetric data from the tops of the mountains, beneath rivers and lakes, to the depths of the sea.

Co-Editors
David F. Maune, PhD, CP and Amar Nayegandhi, CP, CMS

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A Method of Extracting High-Accuracy Elevation Control Points from ICESat-2 Altimetry Data

Binbin Li, Huan Xie, Shijie Liu, Xiaohua Tong, Hong Tang, and Xu Wang

Abstract

Due to its high ranging accuracy, spaceborne laser altimetry technology can improve the accuracy of satellite stereo mapping without ground control points. In the past, full-waveform ICE, CLOUD, and Land Elevation Satellite (ICESat) laser altimeter data have been used as one of the main data sources for global elevation control. As a second-generation satellite, ICESat-2 is equipped with an altimeter using photon counting mode. This can further improve the application capability for stereo mapping because of the six laser beams with high along-track repetition frequency, which can provide more detailed ground contour descriptions. Previous studies have addressed how to extract high-accuracy elevation control points from ICESat data. However, these methods cannot be directly applied to ICESat-2 data because of the different modes of the laser altimeters. Therefore, in this paper, we propose a method using comprehensive evaluation labels that can extract high-accuracy elevation control points that meet the different level elevation accuracy requirements for large scale mapping from the ICESat-2 land-vegetation along-track product. The method was verified using two airborne lidar data sets. In flat, hilly, and mountainous areas, by using our method to extract the terrain elevation, the root-mean-square error of elevation control points decrease from 1.249–2.094 m, 2.237–3.225 m, and 2.791–4.822 m to 0.262–0.429 m, 0.484–0.596 m, and 0.611–1.003 m, respectively. The results show that the extraction elevations meet the required accuracy for large scale mapping.

Introduction

Spaceborne laser altimetry technology can provide high-accuracy elevation control points for stereo mapping (Garvin et al. 1998; Baek et al. 2005; Proulx-Bourque et al. 2013), and thus plays an important role in the accuracy improvement of topographic mapping in areas without ground control points. In the past, full-waveform laser altimetry satellite data, such as ICESat data (Schutz et al. 2005), have been used as the main data source for this technology. With the development of the technology, the ICESat-2 satellite, which was launched in 2018, adopts photon detection technology, which is a new technology that differs from the technology used in the previous laser altimetry satellites (Markus et al. 2017; Martino et al. 2019). ICESat-2’s laser altimeter can emit three pairs of laser beams (532 nm wavelength) at a laser repetition rate of 10 kHz. Each pair consists of one high-energy (strong) beam and one low-energy (weak) beam (4:1 ratio), which form a ground footprint of approximately 17 m in size, and a 0.7 m along-track footprint sampling resolution (Markus et al. 2017; Martino et al. 2019). Compared with ICESat, ICESat-2’s altimeter has a higher spatial resolution and provides more detailed ground contour descriptions, and thus is expected to further improve the application capability of the technology in the field of stereo mapping.

However, the accuracy of the elevation control points provided by laser altimetry remains uncertain due to the influence of the atmosphere, satellite attitude, topography, etc. To solve this problem, researchers have proposed extraction criteria based on evaluation labels according to ICESat’s detection characteristics. These extraction criteria are used in two main types of methods. The first type of method is based on the extraction of high-accuracy footprint elevation data with the use of a threshold judgment using evaluation labels based on their physical meaning (Carabajal and Harding 2006; Huang et al. 2013; Zwally et al. 2008; Proulx-Bourque et al. 2015). For example, the laser footprint elevations with only one peak of echo waveform are retained. The second type of method is based on building a classifier through sample learning with the evaluation labels (Li et al. 2020). Compared to the first type of method, this approach can ensure the accuracy of the extracted footprint elevation and improve the data retention of the extracted results, but the physical meaning of the screening criteria for the evaluation labels is not clear, and the construction cost of the classifier is high because it needs additional samples with known elevation accuracy. Part of the processing of these methods can be used for ICESat-2, such as using digital elevation model (DEM)/digital surface model (DSM) data to remove the outlier of footprint elevation. But, for these methods, the transmit or echo waveform characteristics, which include the echo waveform peak number, the echo waveform gain, and the reflectivity (the ratio of echo energy to transmitted wave energy), are the most important part of the evaluation labels. Due to the different modes of the laser altimeters between ICESat-2 and ICESat, ICESat-2 does not record the echo waveform and is unable to use the correlated evaluation labels. At present, the related studies mainly focus on the analysis of data accuracy of ICESat-2 (Markus et al. 2017; Neuenschwander and Magruder 2019; Neuenschwander and Pitts 2019; Wang et al. 2019; Carabajal and Boy 2020; Dandabathula et al. 2020), where it was established that ICESat-2 can provide footprint elevations for which the required accuracy is 5 cm at a 25 km × 25 km spatial scale, but this is limited to ice-sheet areas with a slope of less than 1 degree. There is hardly any related research about the method of extracting high-accuracy footprint elevation from ICESat-2. It needs to study the influencing factors for ICESat-2 detection.
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Diffuse Attenuation Coefficient (\(K_d\)) from ICESat-2 ATLAS Spaceborne Lidar Using Random-Forest Regression

Forrest Corcoran and Christopher E. Parrish

Abstract

This study investigates a new method for measuring water turbidity—specifically, the diffuse attenuation coefficient of downwelling irradiance \(K_d\)—using data from a spaceborne, green-wavelength lidar aboard the National Aeronautics and Space Administration’s ICESat-2 satellite. The method enables us to fill nearshore data voids in existing \(K_d\) data sets and provides a more direct measurement approach than methods based on passive multispectral satellite imagery. Furthermore, in contrast to other lidar-based methods, it does not rely on extensive signal processing or the availability of the system impulse response function, and it is designed to be applied globally rather than at a specific geographic location. The model was tested using \(K_d\) measurements from the National Oceanic and Atmospheric Administration’s Visible Infrared Imaging Radiometer Suite sensor at 94 coastal sites spanning the globe, with \(K_d\) values ranging from 0.05 to 3.6 \(\text{m}^{-1}\). The results demonstrate the efficacy of the approach and serve as a benchmark for future machine-learning regression studies of turbidity using ICESat-2.

Introduction

Measurement and long-term monitoring of water clarity is an important undertaking in oceanography, marine eco-forecasting, pollution and runoff modeling, and coral-reef ecosystem health assessment (National Academies of Sciences, Engineering, and Medicine 2018). Turbidity, which refers to the capacity of a body of water to attenuate light, has been used across numerous disciplines, including in classifying water types (Jerlov 1976; Sarangi et al. 2002), determining the vertical distribution of algae species (Saulquin et al. 2013), protecting submerged aquatic vegetation and coastal estuaries (Gallegos 2001; Doxaran et al. 2006), and modeling colored dissolved organic matter in shallow estuaries (Branco and Kremer 2005). Spatially and temporally varying measurements of turbidity are also frequently used in airborne bathymetric lidar project planning (Richter et al. 2017; Saylam et al. 2017; Forfinski-Sarkozy and Parrish 2019). One of the most common metrics used to quantify turbidity is the diffuse attenuation coefficient of downwelling irradiance \(K_d\), an apparent optical property (AOP) defined by Equation 1 (Mohley et al. 2020) and typically specified in units of \(\text{m}^{-1}\):

\[
\begin{align*}
K_d(\lambda) &= -\frac{1}{E(\lambda)} \frac{\partial E(\lambda)}{\partial z} \\
&= -\frac{1}{E(\lambda)} \frac{\partial E(\lambda)}{\partial z} \\
&= -\frac{1}{E(\lambda)} \frac{\partial E(\lambda)}{\partial z}
\end{align*}
\]

where \(z\) is depth, \(E\) is downwelling irradiance, and \(\lambda\) is wavelength.

It is important to recognize that \(K_d\) an AOP, is different from the beam attenuation coefficient, defined as \(c(\lambda) = a(\lambda) + b(\lambda)\), where \(a\) is the absorption coefficient and \(b\) is the scattering coefficient. The beam attenuation coefficient is an inherent optical property, whereas \(K_d\) is an AOP, with the distinction between the two being that AOPs depend on both the medium (i.e., the inherent optical properties) and the light field in which they are measured. According to Guenther (2007), for coastal waters \(K_d\) is generally smaller than \(c\) by a factor of 2 to 6 for green light.

Although the validity of the use of \(K_d\) in the Beer–Lambert law (Equation 2, which is a particular solution of the differential equation in Equation 1) has been the subject of discussion in the literature (Gordon, 1989), the Beer–Lambert law is generally assumed to hold for most water types, providing estimates of \(E\) as a function of depth:

\[
E(z) = E_0 e^{-K_d z}
\]

Traditionally, \(K_d\) has been obtained from in situ techniques such as Secchi depth measurements (Guenther 1985; Z. Lee et al., 2015) and submarine photometry (Koenings and Edmundson 1991); however, advances in satellite imaging and the availability of remotely sensed data have allowed for daily, near-global measurements of \(K_d\) (Z.-P. Lee et al. 2005). Currently, data from the European Space Agency’s Medium Resolution Imaging Spectrometer, the National Aeronautics and Space Administration’s (NASA’s) Moderate Resolution Imaging Spectroradiometer, and the National Oceanic and Atmospheric Administration’s Visible Infrared Imaging Radiometer Suite (VIIRS) are used to generate \(K_{a\text{vis}}\) \((K_d\text{ at a wavelength of }490 \text{ nm})\) maps of the Earth’s oceans (M. Wang et al. 2017). The VIIRS instrument aboard the Suomi National Polar-orbiting Partnership and Joint Polar Satellite System-1 and -2 is a passive radiometer used to detect visible and infrared electromagnetic spectra with the objective of measuring global ocean color (M. Wang et al. 2017).

While this category of passive remote-sensing techniques provides an effective method for measuring \(K_d\) over large spatial extents at daily intervals, it relies strictly on observations of water-leaving irradiance and does not directly measure the absorption and attenuation of light at depth. In this study, we propose an active remote-sensing method for measuring \(K_{a\text{vis}}\) \((K_d\text{ at a wavelength of }532 \text{ nm})\) using NASA’s Advanced Topographic Laser Altimeter System (ATLAS) aboard the Ice, Cloud and Land Elevation Satellite-2 (ICESat-2). A key goal is to produce output...
that is compatible with the imagery-based $K\textsubscript{diss}$ data sets and that can be used to fill in the data gaps and sparse areas that often exist in the imagery-based $K\textsubscript{d}$ products near shorelines with high-resolution, active-sensing data. Additionally, the ability of the ATLAS lidar to penetrate the water column (Jasinski et al. 2016) allows for more direct measurement of turbidity at depth. Despite the uncertainty inherent in the VIIRS $K\textsubscript{d}$ data, we consider VIIRS to be a viable source of reference data in this study, due to the fact that VIIRS $K\textsubscript{diss}$ has been well characterized in the literature (Z.-P. Lee et al. 2005; M. Wang et al. 2017) and is already being used for a number of science objectives (Qi et al. 2015; Shi and Wang 2015; M. Wang and Wilson 2017; Liu et al. 2017; van Hooidonk 2020).

The ATLAS instrument, a 10-kHz photon-counting lidar system operating at a wavelength of 532 nm, was the sole instrument aboard the ICESat-2 satellite. At this wavelength, ATLAS is able to penetrate bodies of water up to a depth of approximately 40 m in areas of low turbidity (Parrish et al. 2019). It measures the time of flight of discrete photons reflected by the Earth and the Earth’s atmosphere. A diffractive optical element within the ATLAS system splits each laser pulse into six beams, grouped into three pairs and oriented roughly perpendicular to the satellite flight direction. The beam pairs are separated by approximately 3.3 km across the track, with each pair made up of a strong and a weak beam. The strong and weak beams have an energy ratio of approximately 4:1 and are separated by approximately 90 m in the across-track direction and approximately 2.5 km in the along-track direction. Figure 1 shows the footprint pattern of the ATLAS beams (Neumann et al., 2020a).

Several studies have already demonstrated the ability to extract $K\textsubscript{d}$ measurements from spaceborne lidar systems (Lu et al. 2014, 2019, 2020). However, these studies focus on specific sites of limited spatial extent, making it difficult to generalize their findings to a global scale. Additionally, they rely on deconvolving the received lidar signal using an estimate of the system impulse response function. The ATL13 inland water product also includes a subsurface attenuation coefficient, defined as the sum of the absorption and scattering coefficients and computed as described by Jasinski et al. (2020). In contrast, the techniques used in the present study require minimal signal preprocessing and instead favor an ensemble machine-learning approach to derive $K\textsubscript{diss}$ from patterns in the shapes of ATLAS pseudo-waveforms (vertical histograms representing the number of photons within discrete elevation intervals, used to approximate a full waveform response from the photon-counting point cloud). This technique is advantageous because it does not require knowledge of the system impulse response, deconvolution of the pseudo-waveform, or any curve fitting. Instead, it requires only the computation of a few simple statistical features, which the trained model uses to make predictions. To demonstrate the validity of this technique, we extracted pseudo-waveforms from 543 ground tracks, collected from 94 sites across the world, and performed a random-forest regression between the ATLAS pseudo-waveforms and VIIRS $K\textsubscript{diss}$ measurements (derived from VIIRS $K\textsubscript{diss}$) observed at the same approximate locations and times. The $R^2$ of the regression was 0.67 ± 0.12, with a mean squared error of 0.34 ± 0.14 m$^{-2}$, a mean absolute error of 0.21 ± 0.4 m$^{-2}$, and a mean relative difference of 1.07 ± 0.25, over the range of 0.05 to 3.6 m$^{-2}$, indicating that ATLAS pseudo-waveforms can be used to complement VIIRS $K\textsubscript{d}$ data and fill in data voids, especially in nearshore regions.

This study is the first to report accuracy metrics, aside from the mean relative difference (Lu et al. 2014, 2019, 2020), for $K\textsubscript{d}$ retrieval from a spaceborne lidar system. Therefore, these metrics stand as a benchmark for future studies. Importantly, our assessment of the model’s accuracy does not rely solely on a single training–test split but rather on the average score of a randomized cross-validation approach, making our evaluation robust to any biases introduced by the training–test split and the inherent randomness associated with the convergence of random-forest regression. Figure 2

---

**Figure 1.** Schematic of ground-track pattern made by ICESat-2’s Advanced Topographic Laser Altimeter System lidar. Beams are separated into three pairs of strong and weak. The pairs are separated by 3.3 km, and within each pair, the strong and weak beams are separated by 2.5 km in the along-track direction and 90 m in the across-track direction.
shows an outline of the general workflow used to develop the random-forest regression model for $K_{d532}$.

**Methods**

Bathymetric or topobathymetric lidar has long been used for hydrographic surveys in both inland and nearshore coastal waters (Muirhead and Cracknell 1986). The majority of this research has been conducted using airborne, full-waveform lidar systems which calculate depths (or seafloor elevations, relative to a defined vertical datum) from digitized return waveforms (Walker et al. 1999; Klemas 2011; J. H. Lee et al. 2013; Rogers et al. 2015, 2016; C. Wang et al. 2015; Richter et al. 2017; Saylam et al. 2017). These waveforms typically display two peaks—an upper peak corresponding to the water surface and a lower peak corresponding to the bathymetric bottom—along with an exponentially decaying signal contribution between the two peaks, typically referred to as “volume backscatter” and corresponding to returns from water-column constituents (Guenther 2004). The intensity of the waveform diminishes between these peaks as a result of the water turbidity and can be modeled with an exponential decay function. The decay coefficient of this exponential function represents $K_d$, as can be readily seen from Equation 2.

By contrast, ICESat-2’s ATLAS instrument is a photon-counting lidar system that measures the flight time of discrete photons. As a result, ATLAS does not generate full waveforms but instead produces two-dimensional photon-cloud profiles. In this work, we generated “pseudo-waveforms” that serve the same purpose as waveforms (i.e., to indicate the “energy” or strength of return in vertically binned depth ranges). This was done using a moving window with an along-track length of 20 m and a height of 1 dm. At each decimeter depth interval, we counted the number of photons within the 20-m along-track distance. The count at each interval is proportional to the amplitude of the pseudo-waveform at that depth. By stacking these discrete depth-interval bins vertically, we created pseudo-waveforms from each of the point-cloud profiles in our data set. Finally, we cropped these pseudo-waveforms between −10 and 10 m (an empirically determined range) along the vertical axis to standardize the boundaries of the waveform above and below the water surface. This was a necessary step because it removed unwanted peaks in the waveform above the water surface corresponding to atmospheric phenomena, as well as unwanted peaks below the water surface due to instrument effects or signal noise. All the data used in the study were far enough offshore that bathymetric returns were not considered a factor within the elevation window from −10 to 10 m. Figure 3 shows examples of pseudo-waveforms extracted from the ATLAS data set used in this study.

An important question that arises with respect to Figure 3 is: Why not just directly estimate $K_d$ by fitting an exponential decay curve to the pseudo-waveform? While this is, in theory, possible (at least if field-of-view loss and other system variables...
are accounted for; Guenther 2007), the situation is complicated by the fact that the decay is a function not solely of the volume backscatter but also of the system impulse response function and other system-specific parameters. It should be noted that the sample pseudo-waveforms shown in Figure 3 are fairly “clean” examples; artifacts such as ringing or after-pulsing after the strong water-surface return are often present. In addition, the ATLAS sensor is susceptible to solar-induced background noise, particularly during the daytime, which can affect the signal decay (Neuenschwander and Macgruder 2019; Malambo and Popescu 2020; McGarry et al. 2021).

Based on these considerations, there are two fundamentally different approaches to computing \( K_f \) from ATLAS pseudo-waveforms. The first is to apply deconvolution, noise removal, and/or other signal processing as preprocessing steps before curve fitting and then, if needed, to apply an additional step of converting from the lidar attenuation coefficient to \( K_f \) (Feygels et al. 2003; Churnside 2013; Carr and Tuell 2014; Zhang et al. 2021). This general approach has been tested by others (Lu et al. 2019, 2020). The second approach is to avoid additional preprocessing and simply use the pseudo-waveforms (and/or derived features) “as is” in machine-learning algorithms, which should be able to learn the associations, even in the presence of noise or artifacts. While neither of these two fundamentally different approaches is inherently right or wrong, and both have associated trade-offs, based on experimentation with both we prefer the latter. Its advantages include the fact that it is simpler, avoids extensive preprocessing (which may introduce complications or errors if the preprocessing algorithms are not tuned correctly), is more robust to solar-induced background noise, and does not require knowledge of the system impulse response function, which may not be available and may change over time. Additionally, because of the step in our procedure of training the model with \( K_f \) data, as long as the relationship between the lidar attenuation coefficient and \( K_f \) can be modeled, a separate conversion from the lidar attenuation coefficient to \( K_f \) is unnecessary, as it is inherently accounted for in the training procedure.

**Feature Engineering**

In order to describe the shapes of the pseudo-waveforms, we treated the pseudo-waveforms as statistical distributions and calculated several features of the data: the mean, median, standard deviation, median absolute deviation, skewness, and kurtosis. In addition to these statistical features, we calculated several nonstatistical indices to describe the pseudo-waveforms: the number of peaks, the ratio of the areas under the curve between 0 and \(-1\) m elevation and between \(-1\) and \(-10\) m, and the maximum slope.

Table 1 shows the equations and algorithms used to calculate the features of the pseudo-waveforms. The statistical features are based on statistical moments, which are calculated using Equations 3 and 4 (Parrish et al. 2014), where \( n \) is the distribution mean and \( m_i \) is the \( i^{th} \) moment of the distribution:

\[
\bar{n} = \frac{\sum_{n=0}^{N-1} n \cdot y[n]}{\sum_{n=0}^{N-1} y[n]}
\]

\[
m_i = \frac{\sum_{n=0}^{N-1} (n - \bar{n})^i \cdot y[n]}{\sum_{n=0}^{N-1} y[n]}
\]

One important consideration in calculating these pseudo-waveform statistics and features was the distinction between strong and weak beams in ICESat-2 ground tracks. To determine whether the weak- and strong-beam data could be combined in the modeling process, we segmented the data by beam type and conducted \( t \)-tests on the distributions of the features from the strong versus weak beams, with a significance level of 95%. The \( p \)-values from this analysis (Table 2) indicated that the majority of the waveform features from the strong and weak beams could be considered parts of the same populations with greater than 95% confidence, although low \( p \)-values were noted for the quartiles, median absolute deviation, and number of peaks. Since these features are particularly sensitive to the signal-to-noise ratio, it makes sense that they would differ between the strong and weak beams. Given that the majority of features, including the three with the highest predictive power (kurtosis, standard deviation, mean), met the 95% confidence criteria, we decided to combine the data from the weak and strong beams. This decision had the added benefit of allowing us to generate one model, as opposed to a weak-beam model and a strong-beam model.

**Regression Analysis**

Random-forest (RF) regression is a supervised machine-learning technique used to approximate a function between a set of independent variables (e.g., features) and a continuous dependent variable (e.g., ground truth). It is an ensemble method that builds a large number of decision-tree (DT) predictors that depend on randomly sampled, independent, identically distributed vectors within the feature space (Breiman 2001). Each DT predictor in the forest learns a different mapping from the feature space to the dependent variable, using the Binary Recursive Partitioning algorithm (Cutler et al. 2011). The final prediction of the RF regression model is the average value of the DT predictors; as the number of DT predictors increases, the error of the model converges almost surely (Breiman 2001).

In order to determine the accuracy of the model, the data are first split into training and test subsets. The RF regression model is built using the training data and then applied to the test data. Accuracy metrics can then be calculated by comparing the known values \( y \) of the dependent variable from the test set with the model-predicted values \( \hat{y} \). Due to the inherent randomness of the algorithm, the model generated in one round of training is often not an exact replica of a model generated by a subsequent round of training.

Additionally, different partitions of the data set into training and test subsets introduce different biases into the models.
Table 1. Features of pseudo-waveforms.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
<th>Equation, Pseudo-Code, or Reference for Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUC ratio</td>
<td>The ratio of the AUC between 0 and −1 m to the AUC between −1 and −10 m</td>
<td>$\text{AUC ratio} = \frac{\text{AUC}<em>{0(-1)}}{\text{AUC}</em>{(-1)(-10)}}$</td>
</tr>
<tr>
<td>A/B ratio</td>
<td>The ratio of the AUCs above and below 0 m</td>
<td>$\text{A/B ratio} = \frac{\text{AUC}<em>{\text{Above}}}{\text{AUC}</em>{\text{Below}}}$</td>
</tr>
<tr>
<td>Number of peaks</td>
<td>The number of peaks in the waveform with a prominence greater than 16 (i.e., the saturation point of the ATLAS sensor)</td>
<td>scipy.signal.find_peaks (# photons, prominence = 16) (Virtanen et al. 2020)</td>
</tr>
<tr>
<td>5th percentile</td>
<td>The noise in the waveform as measured by the value separating the smallest 5% of photon counts from the other 95%</td>
<td>$P_i = 0.05N$</td>
</tr>
<tr>
<td>Mean</td>
<td>The center of the waveform as measured by the statistical mean of the distribution</td>
<td>$\mu = \frac{\sum_{i=1}^{N}(i \cdot x_i)}{\sum_{i=1}^{N}x_i}$</td>
</tr>
<tr>
<td>Median</td>
<td>The center of the waveform as measured by the value that separates upper and lower portions of the waveform equally</td>
<td>Median = $\frac{m_{1/2}}{N}$</td>
</tr>
<tr>
<td>Mode</td>
<td>The center of the waveform as measured by the location of the largest photon-counting bin</td>
<td>Mode = Elev. [max (# of photons)]_{index}</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>The spread of the waveform as measured by the square root of the variance (i.e., the second moment of the distribution)</td>
<td>$\sigma = \sqrt{m_{2}}$</td>
</tr>
<tr>
<td>Skewness</td>
<td>The direction and magnitude of the waveform tail as measured by the population skewness</td>
<td>Skewness = $\frac{m_{3}}{m_{2}^{3/2}}$</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>The two-sided magnitude of the waveform tail as measured by the population kurtosis</td>
<td>$\beta_2 = \frac{m_{4}}{m_{2}^{2}}$</td>
</tr>
<tr>
<td>Amplitude</td>
<td>The peak size of the waveform as measured by half the difference between the minimum and maximum</td>
<td>Amp. = $\frac{1}{2}(\text{max}(\text{photons}) - \text{min}(\text{photons}))$</td>
</tr>
<tr>
<td>Maximum slope</td>
<td>The steepness of the waveform as measured by the largest rate of change between consecutive photon bins</td>
<td>Max slope = $\max_{i=3}^{N} (x_i - x_{i-1})$</td>
</tr>
<tr>
<td>Median absolute deviation</td>
<td>The spread of the waveform as measured by the median distance from the mean</td>
<td>MAD = median</td>
</tr>
<tr>
<td>Pearson 1st coefficient</td>
<td>The direction and magnitude of the waveform tail</td>
<td>Pearson 1 = $\frac{\mu - \text{mode}}{\sigma}$</td>
</tr>
<tr>
<td>Pearson 2nd coefficient</td>
<td>The direction and magnitude of the waveform tail</td>
<td>Pearson 2 = $\frac{\mu - \text{median}}{\sigma}$</td>
</tr>
<tr>
<td>$Q_1$</td>
<td>The noise present in the waveform tail as measured by the first quartile</td>
<td>$Q_1 = 0.25N$</td>
</tr>
<tr>
<td>$Q_2$</td>
<td>The shape of the waveform as measured by the second quartile</td>
<td>$Q_2 = 0.50N$</td>
</tr>
<tr>
<td>$Q_3$</td>
<td>The shape of the waveform as measured by the third quartile</td>
<td>$Q_3 = 0.75N$</td>
</tr>
</tbody>
</table>

ATLAS = Advanced Topographic Laser Altimeter System; AUC = area under the curve.

and subsequent accuracy metrics. Because of these two facts, it is common practice to train, test, and retrain a model many times to create a distribution of accuracy metrics that can be used to determine the overall accuracy.

We chose RF regression for this study because of its high level of interpretability compared with other machine-learning methods. In particular, we were interested in understanding the predictive power of the features of the waveform in order to better understand how turbidity affects the distribution of photon returns. We implemented the RF regression model using the RandomForestRegressor method from the Scikit-Learn version 0.23.2 (Pedregosa et al. 2011) package in Python.

**Estimation Process**

We collected ATLAS ground-track data from 94 coastal sites around the world using the OpenAltimetry.org web-based user interface for ICESat-2 data (Neumann et al. 2019, 2020b). Sites were selected based on the availability of corresponding VIIRS $K_{\text{snow}}$ data, with an emphasis on acquiring a wide range of VIIRS $K_{\text{snow}}$ values and good geographic distribution. We focused exclusively on nearshore locations, as these areas are

<table>
<thead>
<tr>
<th>Feature</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUC ratio</td>
<td>0.385</td>
</tr>
<tr>
<td>A/B ratio</td>
<td>0.391</td>
</tr>
<tr>
<td>Number of peaks</td>
<td>0.017</td>
</tr>
<tr>
<td>5th percentile</td>
<td>0.008</td>
</tr>
<tr>
<td>Mean</td>
<td>0.538</td>
</tr>
<tr>
<td>Median</td>
<td>0.540</td>
</tr>
<tr>
<td>Mode</td>
<td>0.540</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>0.360</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.992</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.558</td>
</tr>
<tr>
<td>Amplitude</td>
<td>0.694</td>
</tr>
<tr>
<td>Maximum slope</td>
<td>0.312</td>
</tr>
<tr>
<td>Median absolute deviation</td>
<td>0.009</td>
</tr>
<tr>
<td>Pearson 1st coefficient</td>
<td>0.595</td>
</tr>
<tr>
<td>Pearson 2nd coefficient</td>
<td>0.935</td>
</tr>
<tr>
<td>$Q_1$</td>
<td>0.007</td>
</tr>
<tr>
<td>$Q_2$</td>
<td>0.001</td>
</tr>
<tr>
<td>$Q_3$</td>
<td>0.008</td>
</tr>
</tbody>
</table>
of the greatest interest in ecological and engineering projects that rely on turbidity estimates. Additionally, due to the coarse spatial resolution of passive spaceborne sensors used to map $K_d$, such as VIIRS, these coastal areas represent a significant gap in turbidity data. Figure 5 shows the locations of the ATLAS ground tracks we acquired for this study.

For each ground track in our ATLAS data, we acquired three VIIRS $K_{490}$ values, corresponding to the midpoint and both endpoints, and used the average of these three values as the ground-truth value for that ground track. Coordinates with missing $K_{490}$ values, whether due to atmospheric conditions, sun glint, or satellite orbital patterns, were ignored. In collecting the VIIRS $K_{490}$ values, we selected values that minimized the time difference between the corresponding ATLAS and VIIRS measurements. No two corresponding measurements were taken more than 24 hr apart. For comparison, the range of $K_{490}$ values in this data set was 0.02 to 5.2 m$^{-1}$. This translates to a $K_{532}$ range of 0.05 to 3.6 m$^{-1}$.

We then converted the photon heights for each ground track from ellipsoidal to orthometric heights using the Earth Gravitational Model 2008 geoid model and applied the moving-window binning method with an along-track distance of 20 m and height of 1 dm to generate pseudo-waveforms. (The reasons for converting from ellipsoid height to orthometric height were to remove the water-surface tilt that is common when using ellipsoid heights, due to the geoid gradient, and to set the water-surface height near zero; Babbel et al. 2021). Finally, we truncated each pseudo-waveform between 10 m and −10 m and calculated the set of features described in Table 1.

Next we converted the $K_{490}$ values from VIIRS to $K_{532}$ using the following empirical relationship (Lu et al. 2016):

$$K_{532} = 0.68(K_{490} - 0.022) + 0.054 \quad (5)$$

This conversion allowed for a more direct comparison of the ATLAS-derived $K_d$ and the VIIRS $K_d$, as well as a calculation of $K_d$ in the wavelength native to ATLAS. This is particularly advantageous for future bathymetric studies using ATLAS, because it can be used to estimate the depth of the lidar penetration in the water column, and thus the maximum depth at which bathymetry can be retrieved, for a given area.

Using these features and the $K_{532}$ values calculated from VIIRS, we conducted a preliminary regression using a single DT predictor on all the data with all the features included. Based on the results of this preliminary test, we determined the relative importance of each feature in partitioning the data (Figure 6).

Next we generated a correlation matrix of all the features (Figure 7). Using the correlation matrix and relative feature importances, we systematically trimmed features from the data set by comparing pairs of features with a correlation greater than 0.75 or less than −0.75 and removing the feature with the lesser importance from the data set. The resulting features are shown in Figure 8. The main purpose of this feature reduction procedure was to reduce correlation in the final training data set and avoid overemphasizing particular attributes of the waveforms in the modeling process. However, reducing the number of features in the data...
After each round of training we evaluated the model using the test data and calculated the coefficient of determination ($R^2$), mean squared error (MSE), mean absolute error (MAE), and mean relative difference (MRD):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

(6)

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

(7)

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

(8)

$$\text{MRD} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

(9)

where $\hat{y}_i$ is the model-predicted $K_{\text{d532}}$, $y$ is the VIIRS $K_{\text{d532}}$, and $\bar{y}$ is the average VIIRS $K_{\text{d532}}$.

Equation 6 ($R^2$) is used to determine the amount of variance in the VIIRS $K_{\text{d532}}$ explained by the model. MSE and MAE (Equations 7 and 8) are measures of the error between the $K_{\text{d532}}$ from VIIRS and the model $K_{\text{d532}}$ in units of $m^{-1}$. MRD (Equation 9) is a unitless measure of the error between the VIIRS and model $K_{\text{d532}}$. After the 5000th training round, we computed the averages of these four metrics, which serve as the overall modeling accuracy metrics for the final model.

Finally, we trained a model using the entire data set, which can be used to predict $K_{\text{d532}}$ from future ATLAS data.

**Results**

The results of the model evaluation show that on average, the RF regression model is able to explain $67\% \pm 12\%$ of the variance in $K_{\text{d532}}$. The average MSE of the model is $0.16 \pm 0.06 \, m^{-1}$, with an average MAE of $0.21 \pm 0.03 \, m^{-1}$. The standard uncertainty ($\pm \sigma$) of each of these metrics provides an indication of the ability of the model to generalize to new data. This indicates that the predictions of $K_{\text{d532}}$, made on new data by the final model can be expected to differ from VIIRS $K_{\text{d532}}$ by $0.21 \, m^{-1}$. Additionally, the average MRD is $107\% \pm 25\%$. While this value is substantially larger than the MRD observed by Lu et al. (2020), who reported an MRD of 10%, their geographic and temporal scope was limited to three ATLAS ground tracks collected over a period of 1 month around the Antarctic coast. Additionally, the $K_{\text{d532}}$ values they used covered a relatively narrow, low-turbidity range (0.05 to 0.2 $m^{-1}$), whereas the $K_{\text{d532}}$ values in our training data to be an order of magnitude larger than the VIIRS $K_{\text{d532}}$. The algo-

**Results**

... the accuracy of the final model when applied to previously unseen pseudo-waveform data (which is given instead by the metrics in Figure 9). Though subtle, this difference is extremely important to note for future work building on the results of this study.

Figure 11 shows the residuals of the modeled $K_{\text{d532}}$. The maximum and minimum residuals are 1.63 and $-1.17 \, m^{-1}$, with a mean residual of $-0.01 \, m^{-1}$. The largest residuals are observed between VIIRS $K_{\text{d532}}$ of 0.5 and $1.5 \, m^{-1}$. The algorithm does an especially good job fitting to values lower than $0.5 \, m^{-1}$, likely because the bulk of the training data is clustered between 0.0 and $0.5 \, m^{-1}$. We do not consider the abundance of low $K_{\text{d532}}$ values in our training data to be an...
Figure 9. Distributions of $R^2$, mean squared error, mean relative difference, and mean absolute error scores across the 5000 model training runs.

Figure 10. Comparison of the Visible Infrared Imaging Radiometer Suite (VIIRS) $K_d{532}$ (blue) and the model-predicted $K_d{532}$ (yellow). Ground tracks are shown in ascending sorted order, with the lowest VIIRS $K_d{532}$ on the left and the highest on the right.

Figure 11. Residuals of the modeled $K_d{532}$. 
overrepresentation, but instead an accurate reflection of the distribution of $K_{	ext{ATLAS}}$ on a global scale. It is also worth mentioning that many imagery-based $K_{	ext{ATLAS}}$ retrieval algorithms have been shown to perform poorly in higher-turbidity waters, and it is possible that the larger residuals shown in Figure 11 indicate that this problem persists into the current iteration of the retrieval algorithm (M. Wang et al. 2009; Zhao et al. 2013).

**Conclusion**

Measuring turbidity is an important task in many fields of coastal and oceanographic study. Currently, large-scale efforts to measure turbidity on a global level rely solely on satellite imagery. While these techniques have been shown to be effective, they are unable to measure $K_{	ext{ATLAS}}$ at depth, and rely instead on measurements of water-leaving irradiance. In this study we demonstrated a machine-learning-based approach to extracting $K_{	ext{ATLAS}}$ from the ATLAS instrument aboard NASA’s ICESat-2. Using 543 ground tracks, collected from 94 sites across the world, we generated a regression model with an $R^2$ of 0.67 ± 0.12, an MSE of 0.16 ± 0.06 m$^{-2}$, an MAE of 0.21 ± 0.03 m$^{-2}$, and an MRD of 1.07 ± 0.25. While other studies comparing ATLAS-derived $K_{	ext{ATLAS}}$ and values derived from satellite imagery have reported higher accuracies, our work included data from around the world, rather than a small geographic extent, as well as a wide range of $K_{	ext{ATLAS}}$ values, extending into higher-turbidity waters. The methods developed here have the additional advantages of bypassing the need for knowledge of the ATLAS system impulse response, simplifying the signal preprocessing procedure, being applicable over much wider ranges of $K_{	ext{ATLAS}}$ and providing data comparable to the imagery-based $K_{	ext{ATLAS}}$ data sets, such that they can be merged and used to fill nearshore gaps in the imagery-based products. Additionally, in evaluating the level of agreement between the ICESat-2-derived $K_{	ext{ATLAS}}$ obtained using the methods of this work and the ATLAS $K_{	ext{ATLAS}}$ data, it is important to note that the two are generated using fundamentally different types of sensors (active versus passive) and processing workflows, ensuring their independence. Furthermore, this is the first study to rigorously document the achievable accuracies, and thus it can serve as a benchmark for future studies on extraction of $K_{	ext{ATLAS}}$ from satellite-based lidar.

Another contribution of this study is the development of the suite of pseudo-waveform features, which may be investigated in follow-on work to determine their ability to predict a range of seafloor characteristics (e.g., substrate and cover type) in shallow-water areas. A serialized copy of the final model generated by this study is available at https://github.com/litewith/ICESat-2. By incorporating machine-learning algorithms, such as neural networks, we were able to apply machine-learning algorithms, such as neural networks, in extracting $K_{	ext{ATLAS}}$ from ICESat-2’s ATLAS instrument.

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**References**


Improving Remote Sensing Multiple Classification by Data and Ensemble Selection

S. Boukir, L. Guo, and N. Chehata

Abstract

In this article, margin theory is exploited to design better ensemble classifiers for remote sensing data. A semi-supervised version of the ensemble margin is at the core of this work. Some major challenges in ensemble learning are investigated using this paradigm in the difficult context of land cover classification: selecting the most informative instances to form an appropriate training set, and selecting the best ensemble members. The main contribution of this work lies in the explicit use of the ensemble margin as a decision method to select training data and base classifiers in an ensemble learning framework. The selection of training data is achieved through an innovative iterative guided bagging algorithm exploiting low-margin instances. The overall classification accuracy is improved by up to 3%, with more dramatic improvement in per-class accuracy (up to 12%). The selection of ensemble base classifiers is achieved by an ordering-based ensemble-selection algorithm relying on an original margin-based criterion that also targets low-margin instances. This method reduces the complexity (ensemble size under 30) but maintains performance.

Introduction

Classification methods have been increasingly popular in the remote sensing community for decades, and great efforts have been made in the development of advanced classification approaches to improve accuracy (Lu and Weng 2007). Classification has various environmental applications in earth-observing images (Tso and Mather 2001; Mondini et al. 2011). It helps in conducting land cover mapping at large scales. This cartography is then used for territorial planning purposes and natural-resources management. Environmental programs rely on the interpretation of large volumes of remotely sensed data, typically validated using limited amounts of ground reference data (Lippitt et al. 2008).

The characteristics of the training data are a fundamental consideration in constructing any supervised classifier. Some issues are specific to remote sensing data. First, satellite images present a large amount of data, covering large areas. The ground truth is generally assessed on the field, and thus the training data should be limited. Second, the data can be imbalanced, which means that they are not evenly distributed among classes, especially in urban mapping. This is the case for building and road classes, compared to vegetation classes, which are less present in cities. These challenging issues can be overcome through a multiple-classifier framework based on the ensemble-margin paradigm.

Ensemble learning is a powerful learning paradigm, which builds a classification model by integrating multiple diversified component learners (Rokach 2010; Z.-H. Zhou 2012; Woźniak et al. 2014). The success of ensemble methods arises mainly from the fact that they improve the overall predictive performance. Typically, the ensemble methods consist of two phases: production of multiple classifiers and their combination. An ensemble can be composed of either homogeneous or heterogeneous classifiers. Homogeneous classifiers, which are the most widely used, derive from different executions of the same learning algorithm. Such classification models can be produced, for example, through manipulation of the training instances or the input attributes. Popular methods for producing homogeneous models are bagging (Breiman 1996) and boosting (Freund and Schapire 1999; Saberian and Vasconcelos 2011). A common method for combining an ensemble of classifiers is majority voting, where the class with most votes is the one proposed by the ensemble. In this work, besides the production of multiple learners and their combination, an additional intermediate stage is considered that deals with the reduction of ensemble size before combination: ensemble selection.

The ensemble margin is a key concept in ensemble learning (Smola et al. 2000). It can be applied to both the theoretical analysis and the design of machine-learning algorithms. It can provide extra information for improving classification accuracy, but how to use it has still not yet been fully explored. In this work, we exploit this concept to efficiently and effectively map remotely sensed data at two learning levels: the data level and the classifier level. At each level, this ensemble approach emphasizes the role of lower-margin samples in the learning process at the expense of higher-margin samples, the latter having the least influence on ensemble classification performance:

- At the data level, a novel iterative guided bagging algorithm (Guo et al. 2020), exploiting low-margin instances, allows better handling of huge and imbalanced data sets, which are commonly encountered in remote sensing.
- At the classifier level, an innovative ensemble-selection algorithm (Guo and Boukir 2013), also relying on lower-margin instances, aims at reducing the number of members of the ensemble while maintaining its classification performance. This complexity reduction is crucial in remote sensing applications. Indeed, an ensemble approach usually involves a significant number of base classifiers (typically over 100), which can be impractical for very large data sets.

This important issue has not been thoroughly investigated in remote sensing, despite the computational complexity in classifying remote sensing data. Ensemble methods have been used in remote sensing mostly as classification tools for site characterization (Du et al. 2012; Miao et al. 2012; Zhu et al. 2012; Huang and Zhang 2013; Beligi and Drăguț 2016).
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Persistent Scatterer Interferometry for Pettimudi (India) Landslide Monitoring using Sentinel-1A Images

Hari Shankar, Arijit Roy, and Prakash Chauhan

Abstract
The continuous monitoring of land surface movement over time is of paramount importance for assessing landslide triggering factors and mitigating landslide hazards. This research focuses on measuring horizontal and vertical surface displacement due to a devastating landslide event in the west-facing slope of the Rajamala Hills, induced by intense rainfall. The landslide occurred in Pettimudi, a tea-plantation village of the Idukki district in Kerala, India, on August 6–7, 2020. The persistent-scatterer synthetic aperture radar interferometry (PSInSAR) technique, along with the Stanford Method for Persistent Scatterers (StaMPS), was applied to investigate the land surface movement over time. A stack of 20 Sentinel-1A single-look complex images (19 interferograms) acquired in descending passes was used for PSInSAR processing. The line-of-sight (LOS) displacement in long time series, and hence the average LOS velocity, was measured at each measurement-point location. The mean LOS velocity was decomposed into horizontal east–west (EW) and vertical up–down velocity components. The results show that the mean LOS, EW, and up–down velocities in the study area, respectively, range from −18.76 to +11.88, −10.95 to +6.93, and −15.05 to +9.53 mm/y, and the LOS displacement ranges from −19.60 to +19.59 mm. The displacement values clearly indicate the instability of the terrain. The time-series LOS displacement trends derived from the applied PSInSAR technique are very useful for providing valuable inputs for disaster management and the development of disaster early-warning systems for the benefit of local residents.

Introduction
Landslides are the downslope displacement of a specific mass characterized by debris, rock, or a mixture thereof due to Earth’s gravity or instability of terrain structures. Non-flat terrain structures only exist when there is a balance between restrictive (cohesive and friction) and gravitational forces that prevents the flattening of the terrain. Several researchers have observed and analyzed various mechanisms for relating terrain stability (slope) and pore pressure, especially in rainfall-induced landslide events (Iversen and Major 1986; Johnson and Sitar 1990; Fannin and Jaakkola 1999). A continuously changing environment has a greater influence on the occurrence of rainfall-induced landslides in the short and long terms, both locally and regionally (Glade and Crozier 2010).

The Western Ghats Region (WGR) during the past six decades has been frequently affected by large and catastrophic landslides due to reckless deforestation and urbanization. Catastrophic landslides have been reported in 2020, 2018, 2005, 1997, 1989, 1977, and 1958. Due to changing climatic patterns, the South Indian state of Kerala (a part of the WGR) has experienced heavy monsoon rainfall in the past few years, leading to multiple hazards including several catastrophic landslides and flood events. The monsoon pattern in Kerala used to arrive every year at a specific time in the first or second week of June, but now it shows significant variation—especially in the last two years—with a relatively drier monsoon spell in the month of July and intense rainfall in the month of August. Previously, the spatial and temporal distribution of rainfall were uniform all through Kerala during rainy season. Now the spatial distribution of rainfall had also changed, and there are significant events of localized high-intensity rainfall. In 2018, the rainfall distribution was clustered in the central and southern parts of Kerala (Hunt and Menon 2020), and in 2019 it shifted to the northernmost parts of the state (Krishnan et al. 2020). This year (2020), it was in the eastern part of the state—that is, the Idukki and Wayanad districts (Krishnan et al. 2020). A number of studies have indicated the change in rain pattern over the entire WGR (Mishra et al. 2018; Hunt and Menon 2020; Krishnan et al. 2020; Kulkarni et al., 2020; Wadhawan et al. 2020). The Indian Network for Climate Change Assessment has predicted an increase in atmospheric temperature and extreme precipitation events associated with floods in the WGR due to a rise in sea surface temperature (Sharma and Chauhan 2011).

Various anthropogenic activities have resulted in geometric changes in the form of ground surface movement in the vertical or horizontal directions. These movements can be measured using various techniques such as terrestrial (leveling, high-precision global position system, etc.), photogrammetry, laser scanning, microgravity, and differential synthetic aperture radar interferometry (InSAR) techniques. In situ measurement techniques have limited measurement scope, because of small area coverage, very high costs of field surveying and instruments, and time consumption due to multiple point measurements with limited measurement frequency. Space-based techniques have various advantages over in situ ones, including low cost, fast measurement speed and frequency, and large area coverage. Modern space-based synthetic aperture radar (SAR) systems are capable of acquiring images of a location of interest irrespective of weather conditions and acquisition time, and have multi-frequency, multi-resolution, and multi-polarization capabilities. SAR images give an opportunity to detect and characterize ground surface movement over time with significantly high accuracy.
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