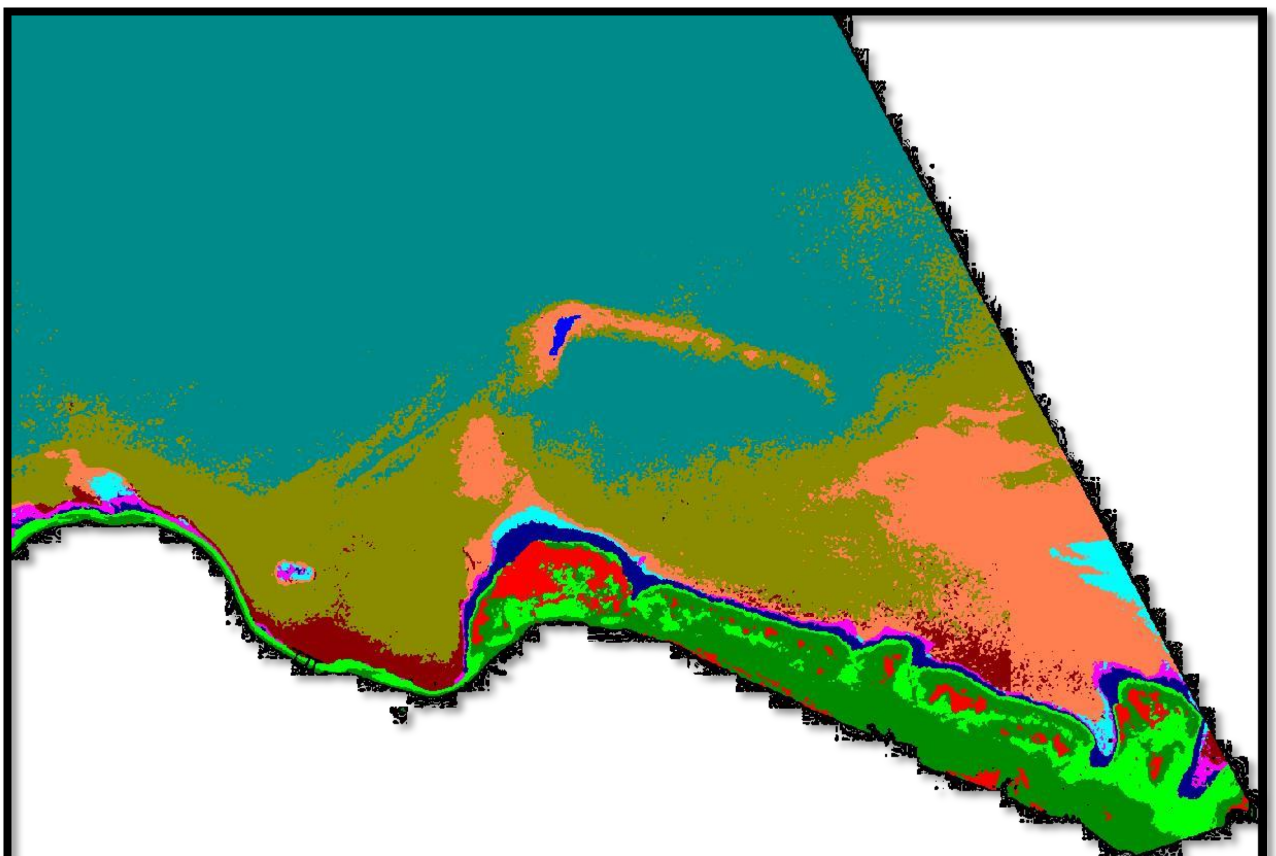
A Methodology for Classification of Benthic Features using WorldView-2 Imagery



On the Cover:

Benthic classification created from the November 2012 water only radiance image (12NOV26022344-M2AS-052717601090_01_P001_REC.tif) using 11 spectra and the Spectral Angle Mapper algorithm in ENVI. The original classification was smoothed and generalized using a 3x3 majority filter passed over the data 3 times, and a 5x5 majority filter passed over once.

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Summary

The objectives of this effort are to *develop and document methods for satellite mapping of benthic habitats using WorldView-2 imagery for Timor-Leste*, as described in Work Order 20150309_Order_WE-133F-15-SE-0518_3K3 LLC, under Task 1.6 of Section 3, *Required Work*. The intent is to review and document methods for deriving benthic habitat information from WorldView-2 satellite imagery. The pilot area for evaluation consists of two images from the north shore of Timor Leste. Methods are developed using standard image processing software (i.e. ENVI and ERDAS Imagine), Excel spreadsheets, and Python scripts. The stated goal is to be able to identify the following habitat types: *hard and soft substrates, the presence of living algae or coral, deep sea (areas too deep to derive meaningful habitat information from the imagery) and mangrove*.

Two widely used methods were chosen as the most feasible approach to develop a benthic habitat classification in Pacific island waters. These are the derivation of a series of depth invariant layers, and an image-based supervised classification procedure. In order to optimize creation of the depth invariant index, a "water-only" image layer is produced using a Normalized Difference Water Index (McFeeters, 1996; Xu, 2006). This layer masks and excludes all "non-water' features, including mangroves. Therefore, mangroves are excluded from any classification output using the depth invariant index. However, mangroves can be identified and delineated using the described supervised classification procedure.

The purpose of this report is to summarize the workflow for a methodology to detect and identify Pacific island benthic habitat classes using WorldView-2 satellite imagery. Based on a review of the literature, the depth invariant index method (DII) was chosen for implementation. The literature review, method, and workflow components are described in this document. In addition, two images were processed using the depth invariant index methods to provide example results. This processing is facilitated by a collection of Python scripts to automate image preprocessing, and ERDAS Imagine Spatial Models to facilitate application of the DII method. It should be noted that this is an iterative process, and that different combinations of DII band pairs, and classification routines may vary by location based on site specific environmental characteristics. In addition, no evaluation of the accuracy of the example image classifications was undertaken, as this was beyond the scope of this project.

Background

Numerous authors have proposed and applied the depth invariant index in nearshore waters as a means to remove the influence of the water column on the characteristics of bottom feature radiance and reflectance. A sampling of these includes: Andrefouet, et al. (2003); Blakey, et al. (2015); Ciampilini, et al., 2015; Deidda and Sanna (2012); Doo et al. (2012); El-Askary (2014); Manessa, et al. (2014); Nieto, 2013); Pahlevan, et al. (2006); and Vanderstraete, et al. (2004). Andrefouet, et al. (2003), provide a description of the concept based on Lyzenga's (1981) work as follows: […]*Lyzenga showed that pixels of the same bottom-type located at various unknown depths appear along a line in the bidimensional histogram of two log-transformed visible bands. The slope of this line is the ratio of diffuse attenuation of the two bands. Repeating this for different bottom types at variable depth results in a series of parallel lines, one for each bottom type. Projection of these lines onto an axis perpendicular to their common direction results in a unitless depth-invariant bottom-index where all pixels from a given bottom-type receive the same index-value regardless of its depth.* The Bibliography section below provides a more comprehensive collection of publications describing the method and its application.

A depth invariant index is calculated using band pairs from a multiband image. Three bands are paired and ratioed iteratively, then combined to produce a multiband image. It should be noted that this method transforms image radiance/reflectance data into a relative index value. This value cannot be directly related to radiance or reflectance values. In addition, it is necessary to have examples of similar bottom types (e.g. sand) present in both shallow and deep water areas within the image. A lack of similar bottom types over a range of depths will bias the resulting ratio values (Maritorena, 1996). Applied in an appropriate area, the method has been shown to increase classification accuracies (Mumby, et al., 1998; Collin, 2012).

Unsupervised classification is a standard image processing method that is widely applied in feature mapping. It is an iterative method that identifies and discriminates natural groupings of spectral signatures within an image. Signature groupings or classes are clustered in two dimensions based on the minimum distance between the individual signatures and the means of signature clusters, as well as between the clusters themselves. Increasing the number of iterations refines the separation of clusters (Andrefouet, et al., 2003; Bejarano, 2010; Boggs et al., 2009; Collin, 2012; Lockie, 2011). Supervised classification relies on a priori or user-selected spectral information in order to “train” the chosen algorithm to identify groupings of spectra that are thought to describe like features. A brief description of the Minimum Distance and ENVI Spectral Angle Mapper (SAM) classification sequences is provided.

Organization

In addition to the Summary and Background sections above, this document includes Methods, and Results and Discussion.

The description of the methods used to calculate the depth invariant index provides details on:

- Image inputs
- ERDAS Imagine command sequences,
- An explanation of the Microsoft Excel template for coefficient calculation
- A brief discussion on image classification

Examples of resulting depth invariant and classified images will be provided in an accompanying PowerPoint file to facilitate evaluation of the results: *depth_invariant_background_and_initial_results.pptx*. possible appendix?

The Results and Discussion section includes recommendations for application of the methods.

Appendix 1 contains a description and the processing sequence for the use of Python scripts for image preprocessing. Appendix 2 describes the ERDAS Imagine command sequence to import and project georeferenced WorldView-2 tiff images. Appendix 3 contains a screenshot of the Bilko-inspired depth invariant index calculation spreadsheet. Bilko is an educational image processing software suite developed by the United Nations Educational, Scientific and Cultural Organization (UNESCO, 1999).

Methods

Figure 1 provides a graphic view of the depth invariant index calculation process, assuming that three bands of a multiband image are used. These bands are labeled 1, 2 and 3 and correspond to the bands listed in Table 1. As this is an iterative process, three depth invariant layers (band pairs) can be derived, 1&2, 1&3, and 2&3. Table 1 below provides WorldView-2 band numbers and names.

Band number	Name
1	Coastal
2	Blue
3	Green
4	Yellow
5	Red
6	Red edge
7	NIR1
8	NIR2

Table 1 band number/name correspondence

Selection of the optimal bands to be combined is a function of the conditions of the local area of interest, including water depth, clarity, and benthic habitat characteristics. Figure 2 provides a partial summary of applications presented in the scientific literature. The type of imagery, level of processing and the bands chosen to derive depth invariant indices are highlighted. It should be noted that the user is not limited to only three band combinations. Collin (2012, p.11) states that […] *These results demonstrated the interspecific spectral variability of corals that could be quantified even with only red, green and blue predictors. However, the addition of two spectral bands, i.e., "coastal" and yellow, allowed for an increase in the power of discrimination of the three coral-dominated assemblages*.

<u>Recommendation</u>:

The graphic below provides guidance as to which bands to begin a classification. However, the "Variation in radiance/reflectance accounted for by depth invariant processing" (box 12 in the Depth Invariant Index Worksheet, Appendix 3), should be used as a guide to select appropriate band pairs. These values are based on image data and compare the coefficient of variation between individual bands and band pairs. This measure indicates which band pairs account for the greatest amount of variation in radiance/reflectance values caused by water column attenuation. The higher numbers identify the band pairs that most effectively account for water column effects.

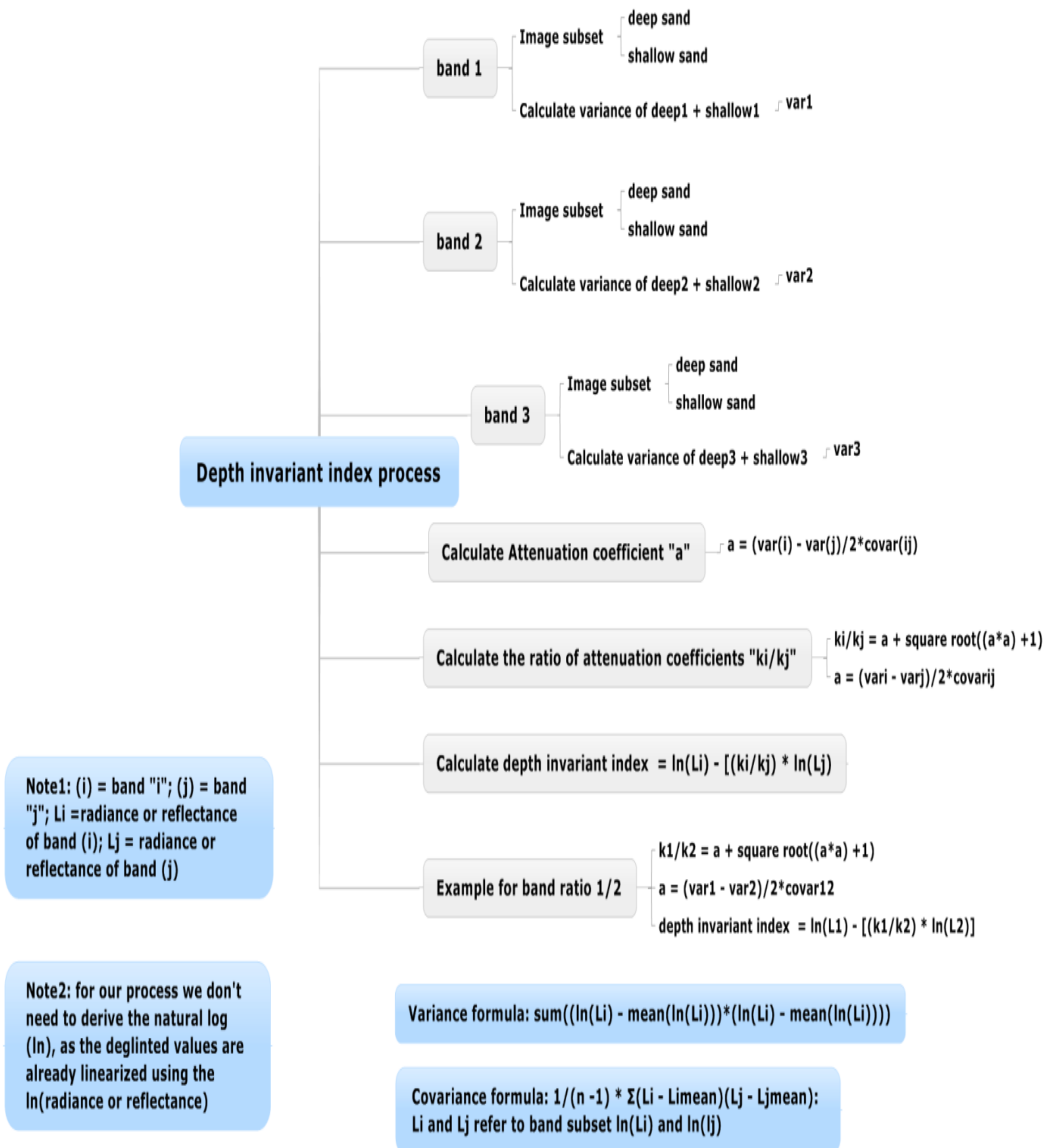

Figure 1 Conceptualization of the depth invariant index calculation

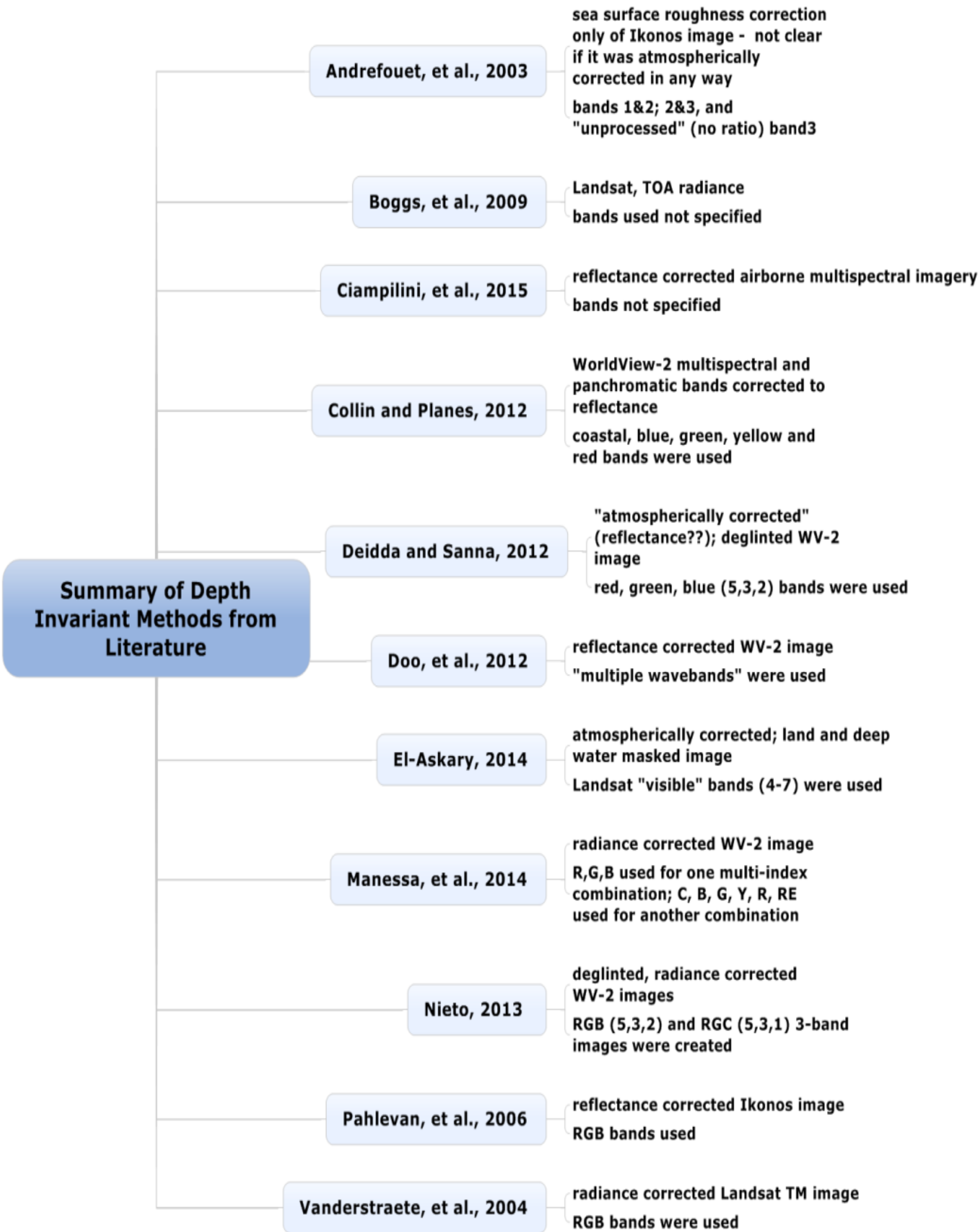

Figure 2 Summary of image bands used to derive depth invariant index

Image Inputs

Required image inputs for creating depth invariant index layers include selected bands of either a raw, radiance or reflectance WorldView-2 image. Radiance values were used to create the examples discussed in this summary. All images used in the process should be:

- Georeferenced
- Deglinted
- Masked for water only features (i.e. all non-water features are masked)

For each image to be processed, at least two image subsets ("AOI" on ERDAS Imagine; alternatively referred to as "ROI" in ENVI) are needed to calculate the coefficients for the index. The subsets should be comprised of largely homogenous areas of known benthic habitat in both shallow and deeper waters. Sandy areas are typically easier to identify and are widely used.

The objective of the depth invariant procedure is to establish the relationship between spectral signatures of similar benthic features at different water depths. These signatures are modified by water column effects, which vary with depth. Therefore, selection of similar features at different depths is crucial to the calculation of depth invariant coefficients.

Generalized Depth Invariant Index Calculation Procedure

The generalized process to follow for the calculation of depth invariant index band pairs is illustrated in Figure 4. For clarity, this procedure is largely drawn from the UNESCO (1999) BILKO tutorial. BILKO is an open source image processing software package. The Depth Invariant Index calculation worksheet contains the formulas used to calculate the various coefficients referred to in Figure 3. In addition, the graphic found in Appendix 3 and in the associated PowerPoint file illustrates typical results of these calculations (*depth_invariant_background_and _initial_results.pptx*).

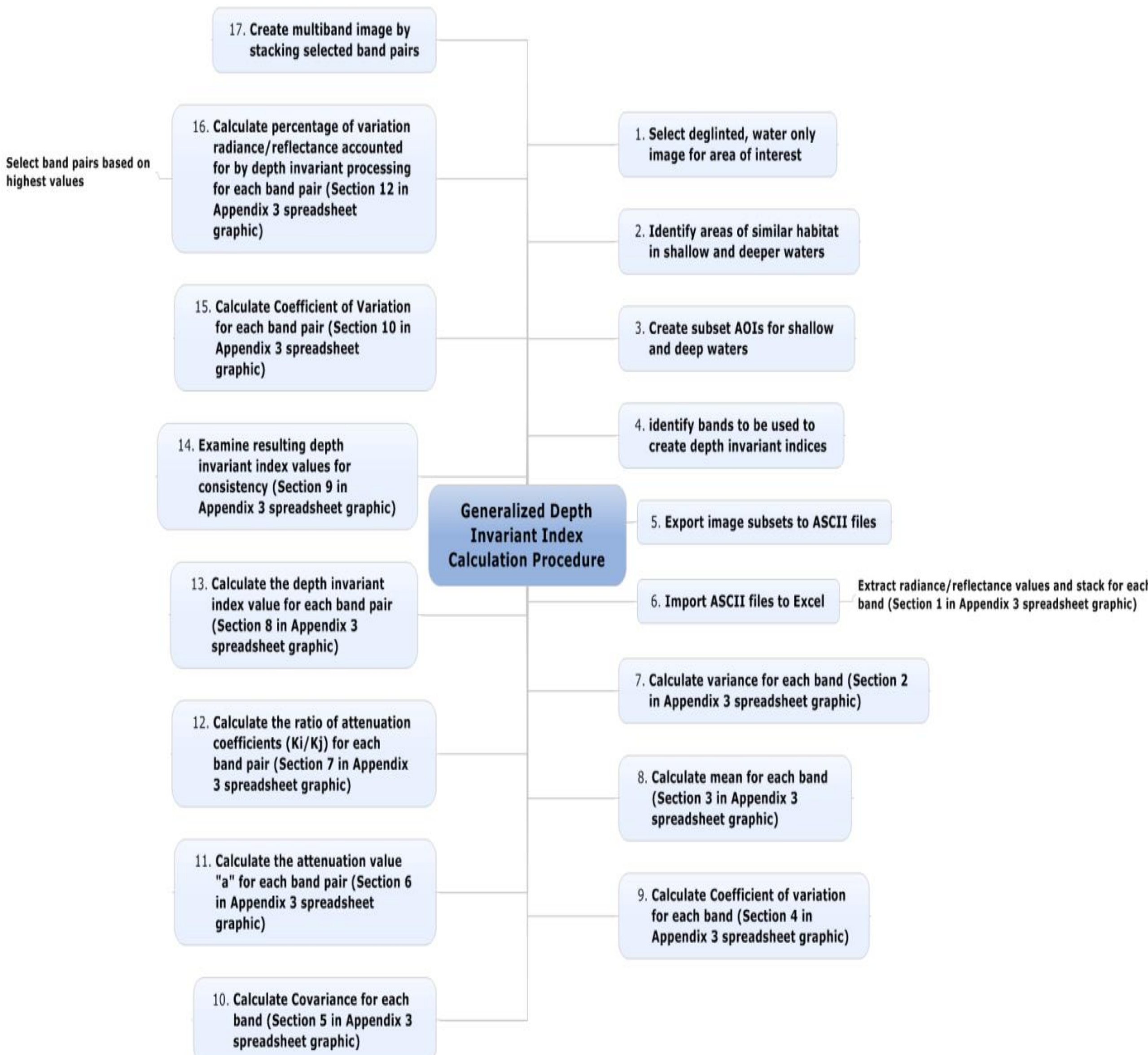

Figure 3 Generalized depth invariant index calculations

Figure 4 describes the ERDAS Imagine command sequence for creating image subsets. Image subsets containing deep and shallow water sand features are used to calculate coefficients to correct for water column effects on benthic feature spectra.

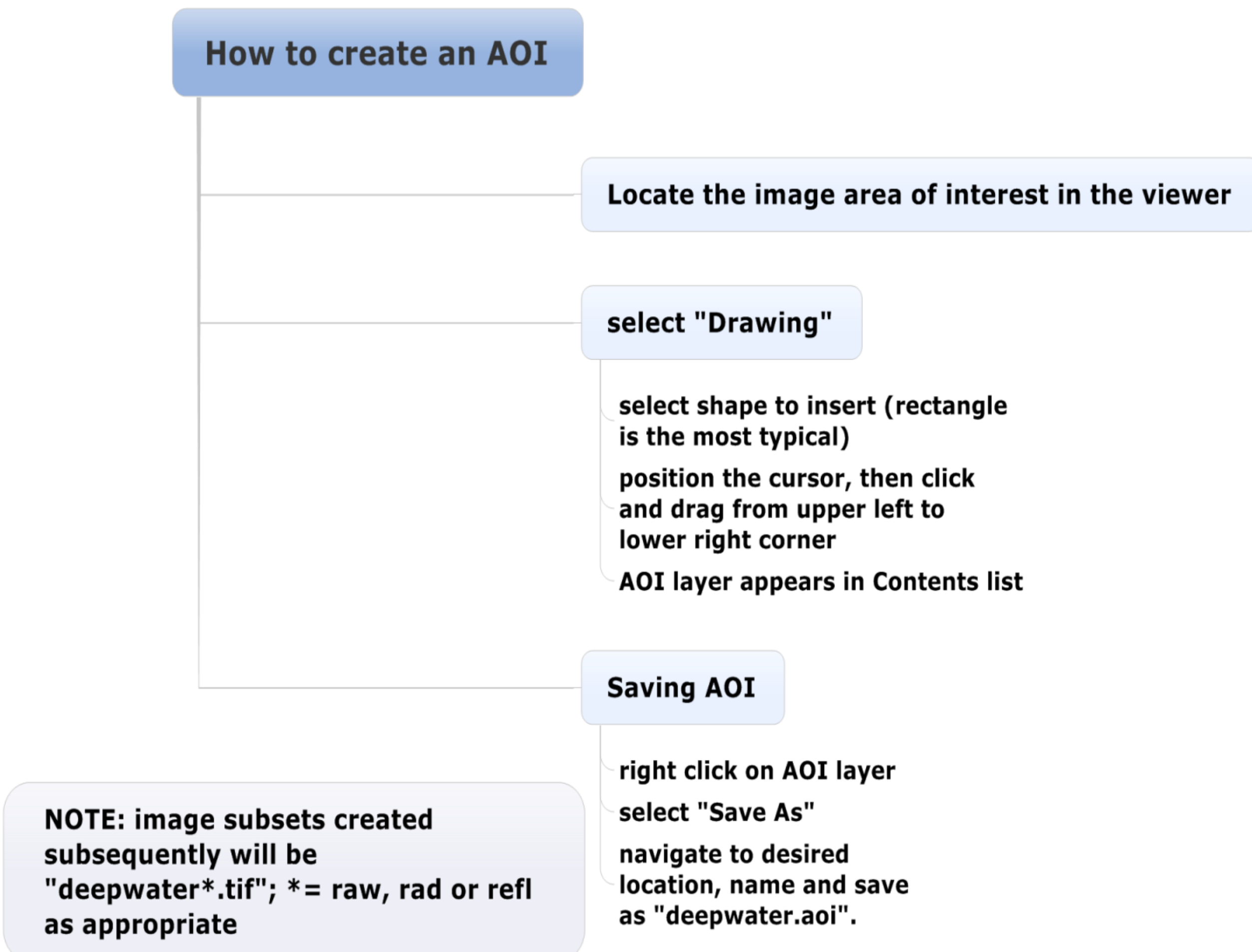

Figure 4 ERDAS Imagine AOI creation command sequence

Models and Scripts

ERDAS Imagine spatial models have been created to automate portions of the depth invariance index calculation and multiband image creation tasks. Descriptions of the models follow below. Figure 5 illustrates the steps to load and run an ERDAS Imagine spatial model.

Deglinted water-only band subset model
This model requires the deglinted, water-only image as an input, and creates individual band files as inputs for calculation of the depth invariant index from band pairs.

Calculation of depth invariant index based on band pairs
This model requires the individual bands from the deglinted water-only image and calculates the depth invariant index for specified band pairs.

Creation of multiband TIF image files
This model "stacks" the specified number of depth invariant bands into a multiband image for classification processing.

Python image pre-processing scripts have been slightly modified to automate the creation of radiance, reflectance, and water only images. These files are listed in Appendix 1, *Image Pre-Processing Python Scripts*.

Scalar Table Recommendation

Scalar tables are created using Notepad or other text editor. The ratio of attenuation coefficients (Ki/Kj) are copied and pasted from the depth invariant index worksheet. The file extension is must be ".sca".

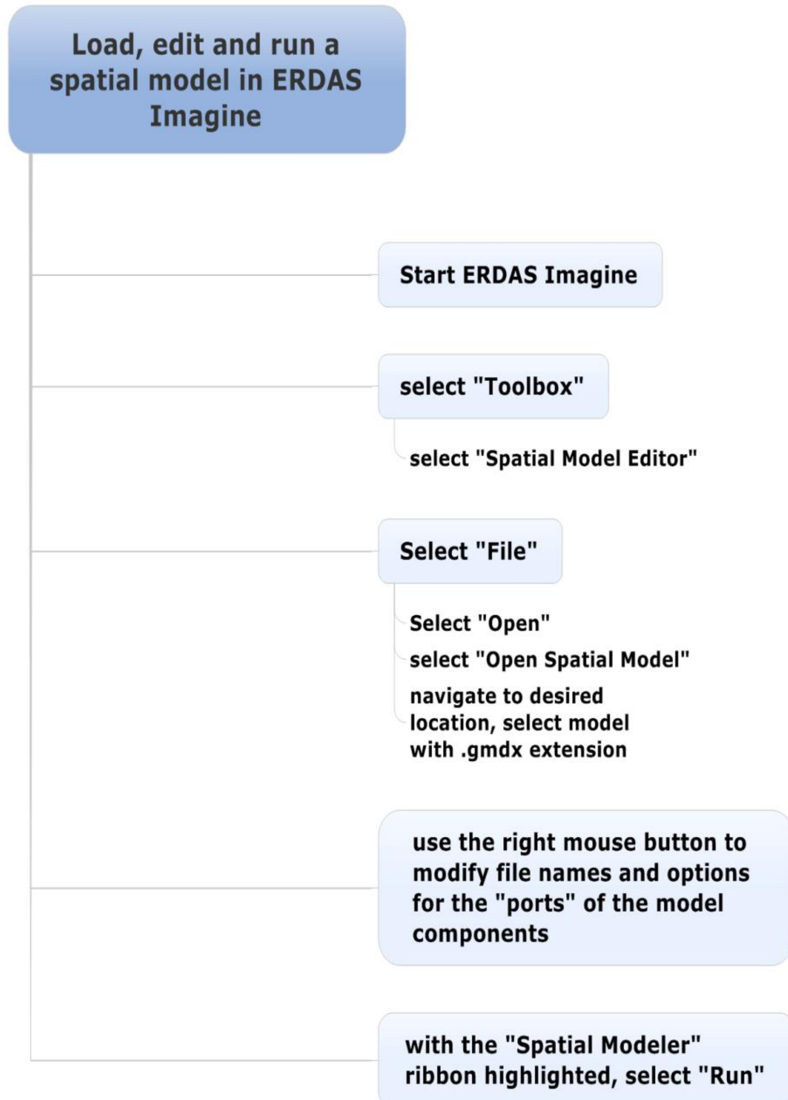

Figure 5 Load and run a spatial model in ERDAS Imagine

Image Classification

Preliminary classification results were generated using unsupervised and supervised classification procedures. ENVI was chosen for this activity due to superior spectral manipulation, analysis, and classification capabilities. The processes described here are found in the *Classification* toolbox in version 5.0 (or *Classification* menu item in ENVI Classic). Results are reviewed in the *Results and Discussion* section.

A multiband depth invariant image was used for evaluation, derived from the WorldView-2 image 12NOV26022344-M2AS-052717601090_01_P001_REC.tif, corrected to top of atmosphere radiance, deglinted and masked for non-water features. Three bands were combined, derived from the 1 & 2, 1 & 5, and 2 & 5 band pairs (Coastal, Blue and Red respectively - see Table 1).

The ENVI K-means module was used to generate an unsupervised result, with 6 and 10 classes specified. The change threshold was set at 5%, maximum iterations was set to 10, and the maximum standard deviation from mean and maximum distance error were not set in order to ensure that all pixels were processed.

ENVI Spectral Angle Mapper (SAM) and Minimum Distance supervised classification procedures (under *Classification => Endmember Collection* in v5.0) were also applied to the depth invariant evaluation image. These procedures require the use of existing spectra in one of several formats that ENVI can read. Using the evaluation image and the spectral profile tool, spectra were collected within the 5, 15 and 20-meter contours and saved as a spectral library. A variety of spectra were chosen, with no particular knowledge of what the underlying features were. These included "open water", sand, and hard bottom. Ideally field data or expert knowledge would guide the selection of spectra for representative features.

For the SAM module, the value for the maximum angle (in radians) was set to 0.100. This angle is used to determine the separation of groups of spectral values. For the Minimum Distance algorithm, the maximum distance error field was left empty, which allows for all pixels to be classified. No rule image was created for either process. A rule image provides what can be thought of as confidence intervals to guide the user in refining the spectral classification. It should be noted that there are numerous classification algorithms to choose from and the user should spend some time learning about these in order to make an informed decision about the best process to use.

Results and Discussion

The purpose of this report is to summarize the workflow for a methodology to detect and identify Pacific island benthic habitat classes using WorldView-2 satellite imagery. Based on a review of the literature, the depth invariant index method (DII) was chosen for implementation. The literature review, method, and workflow components are described in this document. Two images were processed using the depth invariant index methods to provide example results, in the associated PowerPoint presentation: (depth_invariant_background_and_initial_results.pptx). This processing is facilitated by a collection of Python scripts to automate image preprocessing, and ERDAS Imagine Spatial Models to facilitate application of the DII method. It should be noted that this is an iterative process, and that different combinations of DII band pairs, and classification routines may vary by location based on site specific environmental characteristics. In addition, no evaluation of the accuracy of the example image classifications was undertaken, as this was beyond the scope of this project.

Appendix 1 provides a listing and brief description of the Python scripts, developed previously and modified for this application. Appendix 2 provides a graphic illustrating the ERDAS Imagine image import and reprojection workflow. Appendix 3 includes a graphic of the DII calculation Microsoft Excel worksheet and a description of each component part of that worksheet. In addition, graphics of the calculation worksheet and ERDAS Imagine Spatial Models, as well as classification results are included in the associated PowerPoint presentation: (depth_invariant_background_and_initial_results.pptx).

Listed below are recommendations for specific aspects of the DII methodology.

Recommendations

- Reprojection of WorldView-2 images – due to an idiosyncrasy of the combination of Python and Imagine Spatial Models, WorldView-2 images need to be reprojected from the Geographic, WGS84 projection to the UTM projection. The procedure to accomplish this in Imagine is described in Appendix 2, Figure 2-1.

- Number of band pairs to combine – while the trend indicated in Figure 2 is to use three band pairs for classification, Manessa et al. (2014), suggests that using six visible bands improved classification results. As mentioned above, Collin (2012) also suggests that results were improved by combining more than three band pairs prior to classification. In addition, there may be improvements achieved using combinations of band pairs and top of atmosphere (TOA) radiance single bands.

- Ancillary information – benthic habitats are substantially influenced by depth gradients and geomorphological zones (Vanderstraete, 2004). Depth data derived from WorldView-2 data can be used to stratify the image by removing deep water areas and stratifying the remainder by depth. Masks can be created to segment the image and each segment can then be classified independently. Geomorphological zones can also be used in the same fashion. Vanderstraete (2004, p.203) cites slope, aspect, and three dimensional arrangement of reef areas as affecting illumination and areas in shadow, which then influence spectral signature and classification results. Methods for deriving benthic terrain metrics using bathymetric data are provided in Watkins (2015).

- Selection of calibration sites – sandy patches are recommended as calibration sites because they are easy to identify and are typically relatively uniform. Patches in very shallow areas and water deeper than approximately 30m should be avoided. Shallow water sites tend to be oversaturated, and deep water sites are susceptible to absorption of radiant energy.

- Negative depth invariant index values – it is suggested that radiance or reflectance values = zero be excluded from the depth invariant calculations. Deriving a natural log of zero yields a "no data" result. In addition, a negative value has a tendency to skew a classification result. An offset should be added to negative numbers to create a positive range of values (Nieto, 2013, p.41; UNESCO, 1999). Box 10 of the depth invariant index calculation worksheet (Appendix 3, Figure 3-1) lists the minimum value for each band pair so that a positive offset can be determined. This offset is then used to create a scalar table for use in the "create offset band pair images" ERDAS Imagine spatial model.

- Image classification considerations – three methods of classification were applied as part of this effort, K-means (unsupervised), Spectral Angle Mapper (SAM) and Minimum Distance (both supervised). A visual inspection indicated that better results were obtained using the supervised methods. As implemented here, these supervised methods were slightly non-traditional, in that spectral signatures were derived from the images being processed, rather than from field work or existing spectral libraries. It is should be noted that these signatures are based on band ratio indices, not purely radiance or reflectance spectra. In addition, it is important to keep in mind that the boundaries of clusters of spectra that represent habitat features are not always discrete. Oftentimes a gradient, or area of transition is apparent, due to the influence of the radiance/reflectance of adjacent features on the target spectral signatures.

- Classifications of mangroves – in order to optimize the ability to discriminate benthic features, all "non-water" areas were masked out of the image prior to classification. This included mangroves for example, which were one of the features of interest in this project. In order to develop a classification of mangroves, it is suggested that the same supervised approach be taken (e.g. SAM or Minimum Distance), using the full image, or an image that has all water features masked out (this could be accomplished by using the water only image to create a mask). Radiance or reflectance spectra representative of mangroves are then selected based on context – e.g. proximity to the water, "puffy" sort of texture, or bright magenta tone, when using one of the NIR bands to display the multiband composite.

- Post classification filtering – classified imagery typically contains isolated pixels and groups of pixels, presenting a speckled or "salt and pepper" effect. A standard series of steps can be applied to generalize and smooth the classification results. This requires a decision by the user to balance accuracy, utility and aesthetics. Typically, this is an iterative process that involves using filters to change the values of isolated pixels to the majority value of adjacent or enclosing pixel groups, and smoothing the results. It is suggested that this procedure be applied within the ArcGIS environment as the final products are most useful as grid and vector products. The ESRI ArcGIS Help page "Processing Classified Output" (ESRI, 2013) provides a reasonable description of the typical process. Alternatives include the "clump" and "sieve" tools in both ENVI and ERDAS Imagine.

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Appendix 1: Image Pre-Processing Python Scripts

A series of Python scripts, previously created, were modified slightly for this application. There are two primary scripts that are run, *Main.py* and *Main_phase2.py*. Each of these scripts call and sequentially run a series of other Python scripts. Figure 1-1 provides a graphic depiction of how these files are organized, and a brief description of each. In addition, there is the original ReadMe.txt text file that describes the input file requirements, as well as the file structure and organization of the scripts.

The *Main.py* script sets the data processing path; creates top of atmosphere (TOA) radiance and reflectance images; creates a mask file to separate water from non-water portions of the image; creates scalar tables to deglint the "raw image; creates water only raw, radiance and reflectance images; and deglints the "raw" image.

Data requirements for the scripts that are run using this batch file include a "raw" WorldView-2 image; the metadata file for this image (*.IMD); and an image subset of deep water for the scalar table and deglinting calculations. The resultant image subset should be named *deepwaterraw.tif*. Also within the "data" folder are two Perl scripts: russ_helper.pl and russ_v3.pl. These scripts extract coefficients needed for transformation of the raw image data from the "*.IMD" image metadata file.

Once these scripts are complete, the user needs to create deep water image subsets from the water only radiance and reflectance images for input to the next set of Python scripts called by *Main_phase2.py*. These subset images should be named *deepwaterrad.tif* and *deepwaterreflectance.tif* respectively and placed in the "data" folder.

Main_phase2.py calls scripts that create deglinting scalar tables for the radiance and reflectance images; deglints these images; and creates unadjusted bathymetry images using the Stumpf method with the green (#3) and blue (#2) bands.

The resulting deglinted, water only raw, radiance and reflectance images can then be used to create shallow and deep water sand image subsets to calculate depth invariant indices for benthic habitat classification.

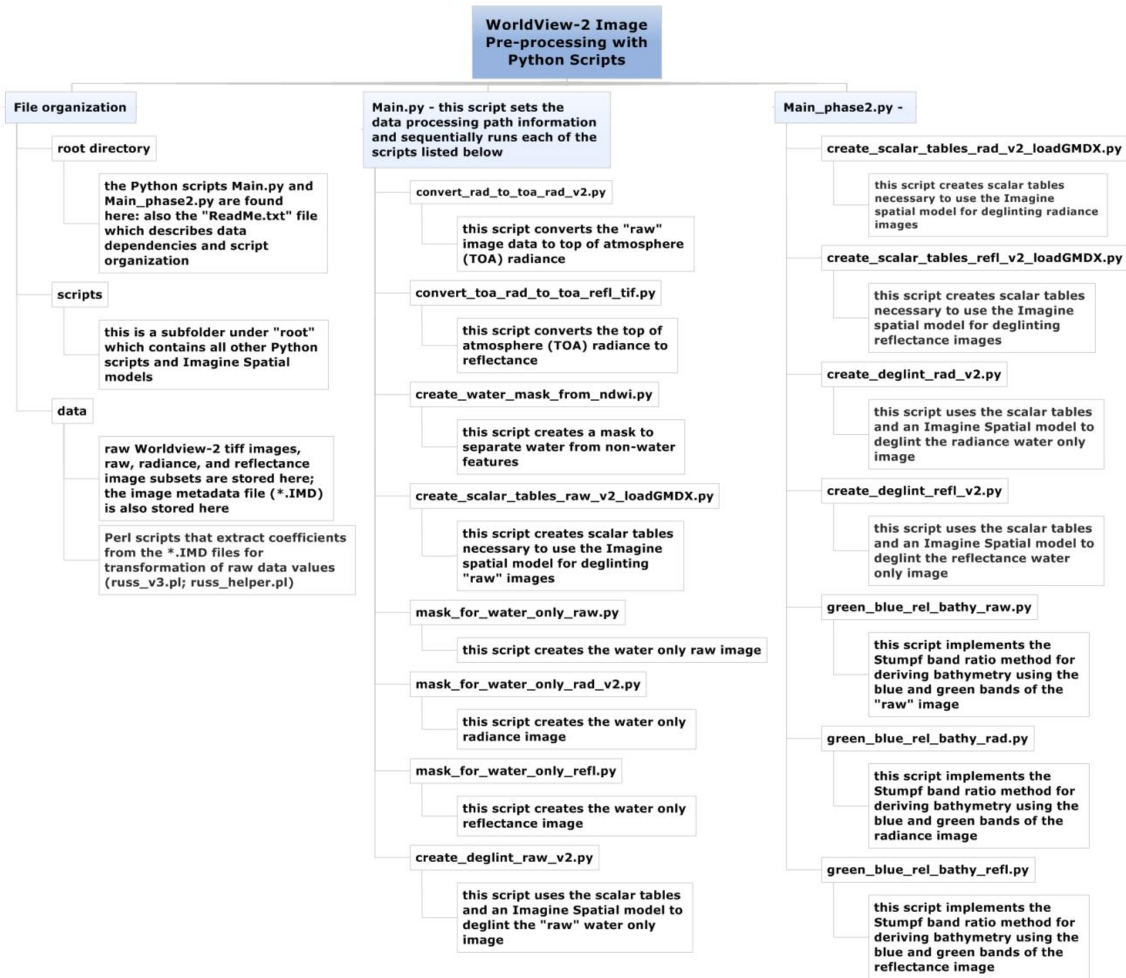

Figure 1-1 Organization of Python image pre-processing scripts

Appendix 2: ERDAS Imagine Command Sequence

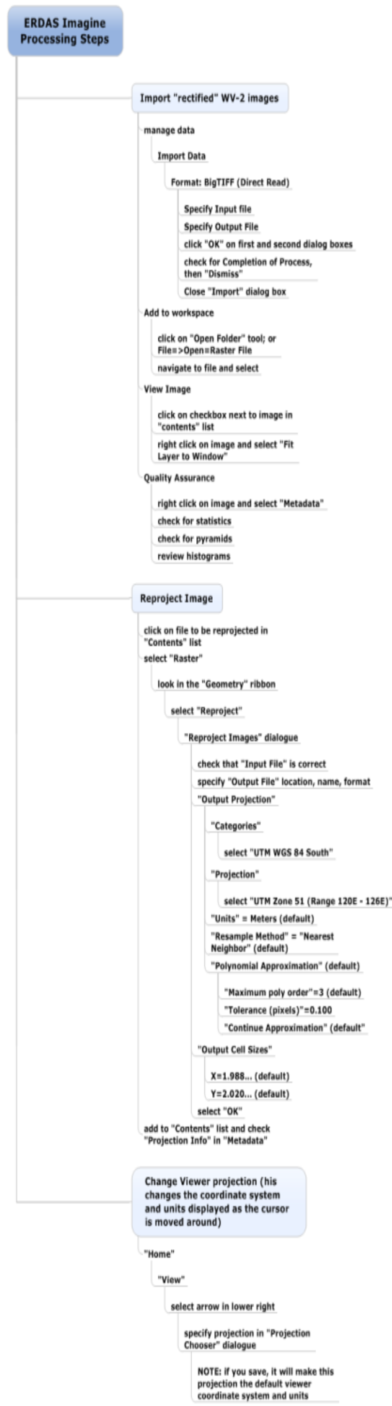

Figure 2-1 ERDAS Imagine Import and Reprojection Command Sequence

Appendix 3: Depth Invariant Index Worksheet

Figure 3-1 is a screenshot of the depth invariant index calculation worksheet. Major components of the worksheet are numbered in red and a list of descriptions by number is on the following page.

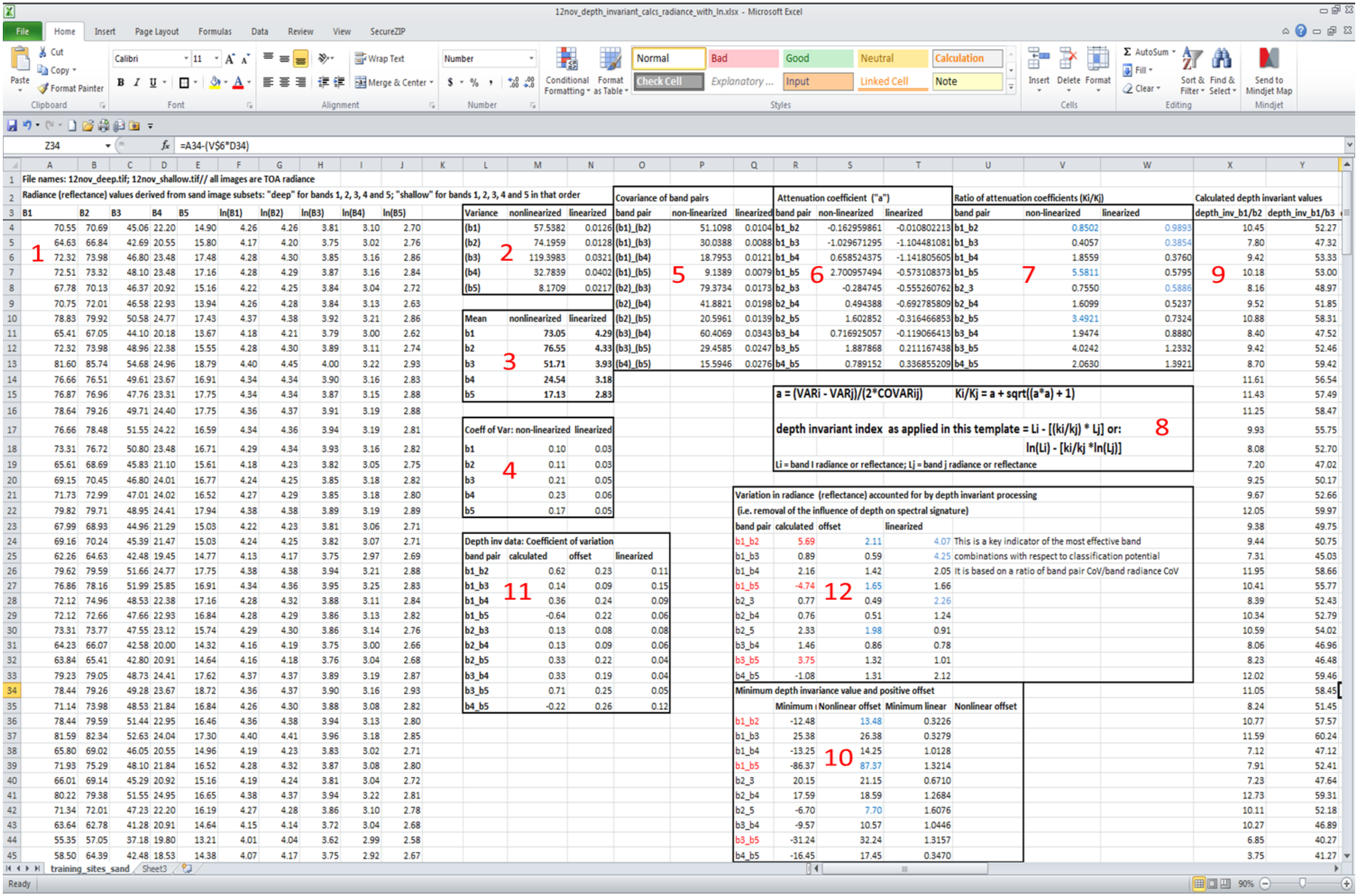

Figure 3-1 Depth Invariant Index Calculation Worksheet

Section descriptions

1. Radiance and/or reflectance values derived from ASCII exports of shallow and deep water image subsets from deglinted, water-only source image, and linearized values derived from natural log of radiance/reflectance values
2. Variance of radiance and/or reflectance values by band
3. Mean of radiance and/or reflectance values by band
4. Coefficient of variation of radiance/reflectance data by band
5. Covariance of all band pair combinations of bands 1 through 5
6. Attenuation coefficient ("a") calculated for all band pairs
7. Ratio of attenuation coefficients (Ki/Kj) calculated for all band pairs
8. Depth invariance index calculation formula (Note: this formula may omit linearization of band radiance/reflectance values if this step occurs in the pre-processing procedure)
9. Example calculated depth invariant values (both initial and offset) using the shallow and deep image subset radiance/reflectance values
10. Minimum values for calculated invariance values and additive offsets to ensure that all depth invariant values are positive
11. Coefficient of variation for invariant index band pairs
12. Variation in radiance and/or reflectance accounted for by depth invariant processing (Note: band pairs with largest values are typically used to create multiband images for classification)

Necessary formulas are embedded in the appropriate sections, and are visible by clicking on a given cell.

Note: for sections 2, 3, 4, and 10, ensure that the range of values used in the calculations matches the range of radiance and/or reflectance values in section 1