Assessing Sentinel-1 Coherence Measures for Tropical Forest Disturbance Mapping

Master Thesis Proposal

Author:

Colm Keyes

Supervisors:

Dr. Johannes Reiche

Dr. Maciej Soja

GRS-80436

Wageningen University & Research

Laboratory of Geo-Information Science and Remote Sensing

January 31, 2023

Contents

1 Introduction

1.1 Background

As biodiversity hotspots and vast sources of carbon, forests are of utmost importance to global climate change resilience. To this end, the REDD+ (Reducing Emissions from Deforestation and forest Degredation) initiative was first commissioned at COP13. REDD+ acts to facilitate the interaction between countries through results based payments, which can be achieved when a country meets certain emissions reduction targets. However, while these targets are clear, forest degradation results have been in deliberation (Pham et al., 2021).

Remote sensing has become an increasingly important tool for forest disturbance mapping in the past decade, though initial monitoring systems have been limited in their detection capacity. Hansen et al., 2016 showed that initial forest monitoring systems based on Moderate Resolution Imaging Spectroradiometer (MODIS) data alone omitted 50% of forest disturbances events detected by Landsat data. Landsat based system Global Land Analysis and Discovery (GLAD) used improved spatial resolution of 30 m, while the spatial resolution of MODIS is 250 m. The improved detection capacity of satellites within the Copernicus programme allows for more advanced applications and further developments in forest monitoring systems. Sentinel-1 is radar system which uses 20 m resolution imagery (Torres et al., 2012).

Recently, there have been a number of developments in SAR based disturbance detection systems. Many of these have shown improved detection results over previous optical systems. Reiche et al., 2021 used the RADD detection system to show that approximately 80% of detected events were of a scale smaller than 0.5 ha. Doblas et al., 2022 used the DETER-R disturbance alerts, detecting some 100,000 ha of additional disturbed forested area over its predecessor, totalling 5% of total detections over the Brazilian Amazon in its first 12 months of operations. These detection systems are governed by backscatter intensity measures, which are defined as the magnitude of the returned Radar signal.

1.2 SAR Coherence

SAR transmits a pulse and listens for the pulse echo. This is different to optical sensors as it can both penetrate clouds as well as operate at night. SAR are active systems, which act as their own sources of radio waves. The advantage of using an active system is that they can be designed for different applications by changing the incident anlge, polarisation and frequency of the transmitted pulse.

SAR images present complex data containing both phase and amplitude measurements. Interferometry refers to the use of the interference between waves. Interferometric synthetic aperture radar (InSAR) exploits the phase difference between two complex SAR observations.

The perpendicular and temporal baselines are important criteria to consider when assessing possible InSAR acquisitions for use. These refer to the perpendicular distance between SAR acquisitions and the temporal difference between them (Hanssen, 2001).

There are two types of SAR interferometry that provide horizontal or vertical velocity information. In the across-track interferometry (XTI) configuration, the phase difference is related to the elevation of the imaged targets on the ground. Thus, XTI is commonly used to map ground topography. In the along-track interferometry (ATI) configuration, the phase difference is related to the radial velocity of the imaged targets on the ground.

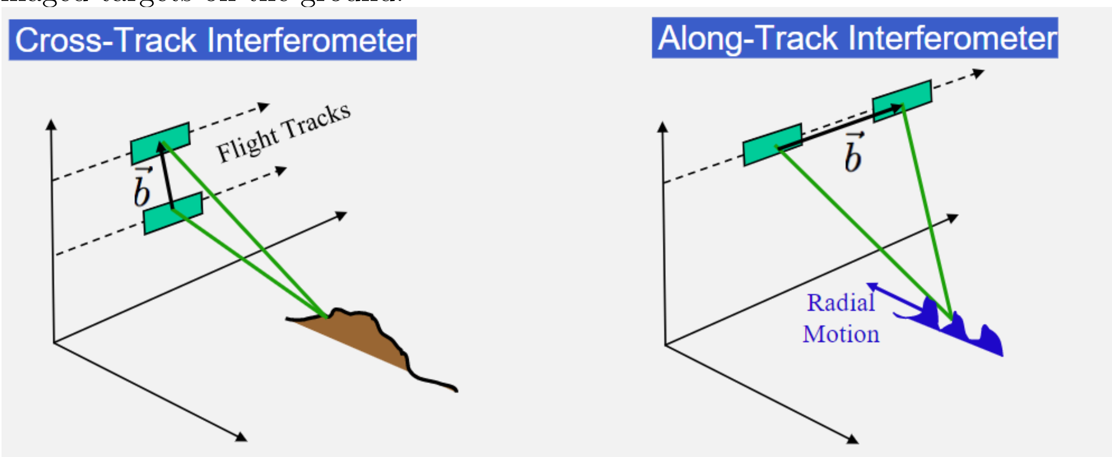

Figure 1: XTI vs ATI acquisition geometry (Fielding, n.d.).

Coherence (or correlation coefficient) is the main InSAR observable (Bamler, 2000). For two complex SAR images S_1 and S_2, it is estimated as:

$$\tilde{\gamma} = \gamma e^{i\Delta\phi} = \frac{\sum_N E|S_1 S_2^*|}{\sqrt{\sum_N E|S_1^2| \sum_N E|S_2^2|}} \tag{1}$$

Where γ is the coherence and $\Delta\phi$ is the phase difference between S_1 and S_2. A spatial averaging window is used to determine the coherence between points, rather than a temporal average, which will contain much more decorrelation affects (Woodhouse, 2017). The complex correlation can be modelled as the product of four decorrelation effects: SNR, system, spatial and temporal decorrelation.

$$\tilde{\gamma} = \gamma_{snr}\tilde{\gamma}_{sys}\tilde{\gamma}_{sp}\tilde{\gamma}_{temp} \tag{2}$$

Using XTI and minimising the temporal baseline, we can determine spatial information $\tilde{\gamma}_{sp}$. In ATI, we minimize spatial errors to determine temporal information $\tilde{\gamma}_{temp}$. γ_{snr} is thermal noise generated by electronics in the satellite. $\tilde{\gamma}_{sys}$ is a more general term used for other possible errors. These may be introduced during SAR processing steps for example. These can be minimised by optimising electronics and processing steps (Kim and van Zyl, 2000 & Hanssen, 2001).

Coherence (or correlation coefficient) is a statistical average of neighboring pixels of similar scattering characteristics. The commonly used algorithm is the boxcar filter, which has the deficiency of indiscriminate averaging of neighboring pixels. The result is that coherence values are lower than they should be.

The correlation between two SAR images is defined by the complex correlation coefficient or complex coherence. For two scattering acquisitions S_1 and S_2, the complex correlation coefficient is defined as:

$$\tilde{\gamma} = \gamma e^{i\Delta\phi} = \frac{E|S_1 S_2^*|}{\sqrt{E|S_1^2|E|S_2^2|}} \tag{3}$$

Where $\Delta\phi$ = interferometric phase or phase difference between two images and E is the electric field vector (Kim & van Zyl, 2000). The complex correlation is the product of four decorrelation effects: SNR, systematic, spatial and temporal decorrelation.

$$\tilde{\gamma} = \gamma_{SNR}\tilde{\gamma_{sys}}\tilde{\gamma_{sp}}\tilde{\gamma_{temp}} \tag{4}$$

Using XTI, we minimize temporal errors to determine spatial information $\tilde{\gamma_{sp}}$. In ATI, we minimize spatial errors to determine temporal information $\tilde{\gamma_{temp}}$. γ_{snr} is thermal noise generated by electronics in the satellite. This can be minimized using a low pass filter. $\tilde{\gamma_{sys}}$ is a more general term used for other possible errors. These may be introduced during SAR processing steps for example. These can be minimised by optimising electronics and processing steps.

HOA

InSAR methods wish to estimate Δh between two acquisitions. Therefore the range difference ΔR must be accounted for, which is removed by a method called radiometric correction, or terrain flattening. This reduces variance due to varying terrain angles and difference in inclination angle. To remove the $2\pi n$ contribution to the change in phase, a complicated and costly process termed phase unwrapping is applied. This operation will not be employed here, as it is not necessary to fully unwrap the phase to determine height differences. Instead, the height of ambiguity measure is introduced:

$$HOA = \frac{2\pi R sin\theta_0}{mkB_{perp}} \tag{5}$$

Where Θ_0 is the incidence angle, m is a constant, k is the vertical wavenumber and B_{perp} is the perpendicular baseline distance. This measure dictates the limit to which a change in height can be determined without an unwrapped interferogram.

2 Research Needs

It is clear from previous work that different temporal baselines can be used to determine different types of useful SAR information (Borlaf-Mena et al., 2021, Akbari and Solberg, 2022, Mestre-Quereda et al., 2020 & Pulella et al., 2020).

Borlaf-Mena et al. (2021) showed that the introduction of long-term coherence reduced the misclassification of forest as urban, while the introduction of short-term coherence reduced the misclassification of low vegetation areas as forest. Akbari and Solberg (2022) demonstrated that coherence magnitude was the stronger predictor of clear-cut areas in eastern Ireland when backscatter intensity and coherence were compared. This indicates that not only there is a temporal aspect to coherence that can be exploited, but that in some cases coherence may be a better tool for inspecting forest disturbance events than backscatter.

There are also a number of instances where backscatter intensity may change significantly with minimal change in forest ground composition (Engdahl et al., 2001 & Wagner et al., 2008). A clear instance is following a heavy shower, where dielectric properties of foliage or soil will change (Vaca & van der Tol, 2018). Another instance is an increase in backscatter due to double bounce of exposed tree trunks after logging, or a significant drop in backscatter due to a forest becoming inundated (Shimada et al., 2014). Reiche et al. (2021) showed that in swampy forest regions, seasonal inundation caused excessive changes in backscatter intensity.

This demonstrates that there are limits to using backscatter measures alone for forest disturbance mapping. A possible way of reducing these errors may come from combining coherence and backscatter measures.

When studying different crop classifications, Mestre-Quereda et al. (2020) found that while both coherence and backscatter performed well at classifying a set of different crop types, there was a significant improvement in results when these measures were combined. It has also been established that coherence is a better biomass indicator when used in seasonal boreal forests, but that both information sources give complimentary data (Koskinen et al., 2001 & Singh et al., 2020).

This illustrates that when investigating areas with varying vegetation responses, coherence and backscatter features are complimentary to one another, increasing the overall information available.

With both coherence and backscatter measures exhibiting disadvantages for use in circumstances which occur frequently in nature, this adds to the need for both measures to be utilised in combination to counteract their individual limitations. Combining both maximises the potential of Sentinel-1 data for forest monitoring applications and minimises its contributing errors.

3 Overall Research Aim and Research Questions

Research Aim: To evaluate interferometric coherence measures for forest disturbance mapping.

Research Question 1: What is a suitable SNAP processing chain for Sentinel-1 SLC data that obtains high resolution data while retaining low coherence bias?

Research Question 2: What are the temporal coherence characteristics of a range of forest disturbance events confirmed by the RADD alert system?

Research Question 3: Using supervised classification methods, how do coherence, backscatter and a combination of both compare for forest disturbance detection in areas of existing RADD alerts?

4 Method

4.1 General Methodology

Study Area:

The study area will comprise of a number of SAR acquisition tiles over the Central Kalimantan region of Indonesia on the island of Borneo, known for its intensive logging activities. Using the Global Forest Watch platform this area was selected as it exhibits clear-cut forested areas, detected by the RADD layer of the integrated deforestation alert system. Particular interest is given to a number of events that occured between February 2021 and March 2022. A diversity of events ranging in size and characteristics will be determined and analyzed.

Data Acquisition:

Sentinel-1 single look complex(SLC) data is freely available from the Alaskan Satellite Facility (ASF) Vertex data portal, in a number of preprocessed forms. Reference data is available freely from the Global Forest Watch platform. From here, RADD alert detections will be obtained for a range of dates corresponding to forest disturbance events in the study area.

Backscatter Processing:

Data will be obtained in the form of Sentinel-1 SLC products from ASF Vertex platform between the dates indicated. Following this, a Graph Processing Framework (GPF) will be built in SNAP and SNAPPY, for preprocessing of SLC products. The preprocessing GPF is then applied to calibrate SLC products. From these preprocessed products a multi-temporal stack for backscatter analysis will be constructed. A multi-temporal speckle filter will then be applied to reduce speckle errors.

Inteferometric Coherence Processing:

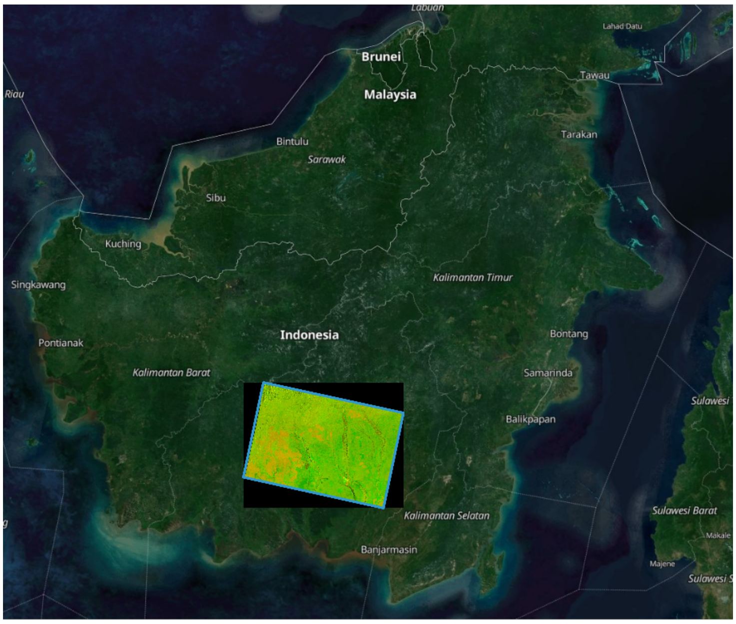

Figure 2: Example of acquisition over Borneo, available from ASF Vertex.

Timeframes will be defined for short and long temporal baslines, with the perpendicular baselines minimized between acquisitions. Appropriate Sentienl-1 SLC products will be downloaded from ASF Vertex platform for dates indicated. Corresponding acquisitions for analysis are first coregistered to form an image stack and split. Preprocessing is then completed using orbital information, back geocoding and the enhanced spectral diversity operator if more than one burst is selected.

Following this preprocessing a coherence estimate can now be produced. Within SNAP, the coherence estimation operator is used. It is important in this step to account for the pixel spacing of Sentinel-1 SLC data, to create an approximately square pixel following coherence estimation. With the coherence estimated, an analysis of the coherence statistics over disturbed areas can be conducted. Time series analysis will be conducted using SNAP and Python packages.

Supervised Classification:

Classification algorithms such as random forest will be used here to classify areas which have similar temporal characteristics to confirmed forest disturbances. Training and test data must be determined for model training. When comparing algorithms, metrics such as f1 score, precision and recall will be utilised.

4.2 Methods

Research Question 1:

There are a number of steps involved in building a suitable coherence processing pipeline. Firstly, a variety of forest disturbance events will be chosen. These will vary in size and composition. The timing of these events is also important to note, given that each will not occur at the same time.

Using SNAP and SNAPPY, a processing pipeline will be built to obtain coherence estimates for the areas. Here, different temporal and perpendicular baselines, as well as different window sizes, must be compared. At least three combinations of range and azimuth window sizes will be tested: 5x1, 10x2 and 15x3. Both the temporal and perpendicular baselines should be minimised, but in practice this may not always be possible, thus a balance must be determined that maximises the snr.

Research Question 2:

There are two main steps involved in this question. Using SNAP and Python, a time series analysis pipeline will be built to measure the change in coherence over the time frame of a disturbance event. Following this, the temporal characteristics of a range of different events will be analysed and compared.

Research Question 3:

There are a number of steps to tackle when answering this research question. SNAP and SNAPPY will firstly be used to process backscatter data from Sentinel-1 SLC acquisitions. From here, supervised classification algorithms will require providing training data of target areas. A number of areas will be selected that exhibit forest disturbance events over the selected time series. This classification will be conducted using coherence and backscatter intensity individually as well as combined.

A number of classification algorithms may be compared here, with a particular eye for the use of convolutional neural networks, if permitted by time constraints. An important measure to be determined here is what signifies a sufficient change to confirm a detection.

5 Time Schedule

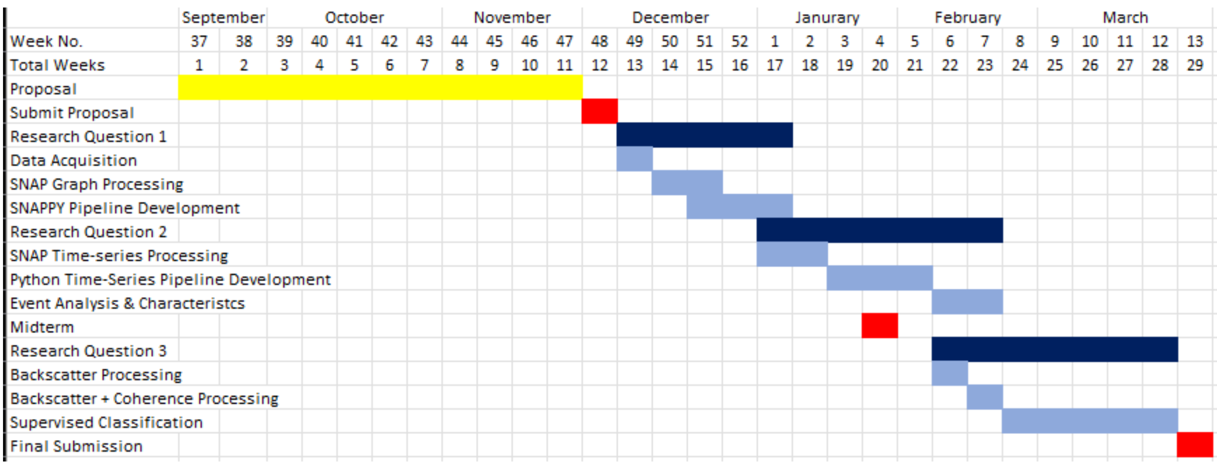

Figure 3: Grant Chart with proposal in yellow, important dates in red and timelines for research questions in dark and light blue.

Progress evaluation meeting scheduled for 16/12/2022, midterm presentation is scheduled for 25/01/2022 and final thesis report due on 28-03-2023.

6 Feasibility

Research Question 1:

A significant issue at this stage of the process may be that coherence estimates are insufficient or too noisy to determine usable information. This can be mitigated aggregating over larger spatial windows, at the expense of spatial resolution. The number of acquisitions may need to be expanded if a sufficient number of events are not detected between two images.

Research Question 2:

The time-series analysis may be more difficult to build into a full processing pipeline in Python, particularly if different sets of acquisitions are used. Processing may be CPU and RAM intensive at this step.

Research Question 3:

This section has the potential to take the most time, since it has quite the open end with the possibility to compare classification algorithms. There may be difficulty combining the coherence and backscatter data sources together. There may also be difficulty building a sufficient number of training samples for the classification algorithms. The training stage of the algorithms will be time consuming, given that these can often require tailoring to a problem before they operate effectively. Here the use of a Convolutional Neural Network will be considered at the classification stage, which will be pursued only if time permits.

References

Akbari, V., & Solberg, S. (2022). Clear-cut detection and mapping using sentinel-1 backscatter coefficient and short-term interferometric coherence time series. *IEEE Geoscience and Remote Sensing Letters*, *19*, 1–5. https://doi.org/10.1109/lgrs.2020.3039875

Bamler, R. (2000). *Surveys in Geophysics*, *21*(2/3), 147–157. https://doi.org/10.1023/a:1006790026612

Borlaf-Mena, I., Badea, O., & Tanase, M. A. (2021). Assessing the utility of sentinel-1 coherence time series for temperate and tropical forest mapping. *Remote Sensing*, *13*(23), 4814. https://doi.org/10.3390/rs13234814

Doblas, J., Reis, M. S., Belluzzo, A. P., Quadros, C. B., Moraes, D. R. V., Almeida, C. A., Maurano, L. E. P., Carvalho, A. F. A., Sant'Anna, S. J. S., & Shimabukuro, Y. E. (2022). DETER-r: An operational near-real time tropical forest disturbance warning system based on sentinel-1 time series analysis. *Remote Sensing*, *14*(15), 3658. https://doi.org/10.3390/rs14153658

Engdahl, M., Borgeaud, M., & Rast, M. (2001). The use of ers-1/2 tandem interferometric coherence in the estimation of agricultural crop heights. *IEEE Transactions on Geoscience and Remote Sensing*, *39*(8), 1799–1806. https://doi.org/10.1109/36.942558

Fielding, E. (n.d.). *Arset*. https://appliedsciences.nasa.gov/sites/default/files/Session4-SAR-English%5C_0.pdf

Hansen, M. C., Krylov, A., Tyukavina, A., Potapov, P. V., Turubanova, S., Zutta, B., Ifo, S., Margono, B., Stolle, F., & Moore, R. (2016). Humid tropical forest disturbance alerts using landsat data. *Environmental Research Letters*, *11*(3), 034008. https://doi.org/10.1088/1748-9326/11/3/034008

Hanssen. (2001). *Remote sensing and digital image processing* (G. Gutman, A. C. Janetos, C. O. Justice, E. F. Moran, J. F. Mustard, R. R. Rindfuss, D. Skole, B. L. Turner, & M. A. Cochrane, Eds.). Springer Netherlands. https://link.springer.com/book/10.1007/0-306-47633-9

Kim, Y., & van Zyl, J. (2000). Overview of polarimetric interferometry. *3*, 231–236 vol.3. https://doi.org/10.1109/AERO.2000.879850

Koskinen, J., Palliainen, J., Hyyppa, J., Engdahl, M., & Hallikainen, M. (2001). The seasonal behavior of interferometric coherence in boreal forest. *IEEE Transactions on Geoscience and Remote Sensing*, *39*(4), 820–829. https://doi.org/10.1109/36.917903

Mestre-Quereda, A., Lopez-Sanchez, J. M., Vicente-Guijalba, F., Jacob, A. W., & Engdahl, M. E. (2020). Time-series of sentinel-1 interferometric coherence and backscatter for crop-type mapping. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 4070–4084. https://doi.org/10.1109/jstars.2020.3008096

Pham, T. T., Moeliono, M., Yuwono, J., Dwisatrio, B., & Gallo, P. (2021). REDD finance in brazil, indonesia and vietnam: Stakeholder perspectives between 2009-2019. *Global Environmental Change*, *70*, 102330. https://doi.org/10.1016/j.gloenvcha.2021.102330

Pulella, A., Santos, R. A., Sica, F., Posovszky, P., & Rizzoli, P. (2020). Multitemporal sentinel-1 backscatter and coherence for rainforest mapping. *Remote Sensing*, *12*(5), 847. https://doi.org/10.3390/rs12050847

Reiche, J., Mullissa, A., Slagter, B., Gou, Y., Tsendbazar, N.-E., Odongo-Braun, C., Vollrath, A., Weisse, M. J., Stolle, F., Pickens, A., Donchyts, G., Clinton, N., Gorelick, N., & Herold, M. (2021). Forest disturbance alerts for the congo basin using sentinel-1. *Environmental Research Letters*, *16*(2), 024005. https://doi.org/10.1088/1748-9326/abd0a8

Shimada, M., Itoh, T., Motooka, T., Watanabe, M., Shiraishi, T., Thapa, R., & Lucas, R. (2014). New global forest/non-forest maps from ALOS PALSAR data (2007–2010). *Remote Sensing of Environment*, *155*, 13–31. https://doi.org/10.1016/j.rse.2014.04.014

Singh, A., Kushwaha, S. K. P., & Kumar, S. (2020). Backscatter and coherence analysis using space borne c-band data for forest characterization. *14*, 39–48.

Torres, R., Snoeij, P., Davidson, M., Bibby, D., & Lokas, S. (2012). The sentinel-1 mission and its application capabilities. *2012 IEEE International Geoscience and Remote Sensing Symposium*. https://doi.org/10.1109/igarss.2012.6351196

Vaca, C. C., & van der Tol, C. (2018). Sensitivity of sentinel-1 to rain stored in temperate forest. *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, 5330–5333. https://doi.org/10.1109/IGARSS.2018.8517859

Wagner, W., Pathe, C., Doubkova, M., Sabel, D., Bartsch, A., Hasenauer, S., Blöschl, G., Scipal, K., Martınez-Fernández, J., & Löw, A. (2008). Temporal stability of soil moisture and radar backscatter observed by the advanced synthetic aperture radar (ASAR). *Sensors*, *8*(2), 1174–1197. https://doi.org/10.3390/s80201174

Woodhouse, I. H. (2017). *Introduction to microwave remote sensing*. CRC Press. https://doi.org/10.1201/9781315272573