DSC180 Papers

- **Useful links**
    - https://earth.esa.int/dragon/LeToan1_SAR_scattering_physics.pdf (intro to sar)
    - https://earthdata.nasa.gov/learn/backgrounders/what-is-sar (intro to sar)
    - https://earthdata.nasa.gov/earth-observation-data
    - http://www.wfas.net/ (Lots of data on fire danger, weather, moisture, etc.)
    - https://github.com/mortcanty (Cool articles on statistical change detection)
    - https://burnseverity.cr.usgs.gov/ (Lots of burn severity resources)
    - https://www.mtbs.gov/ (burn severity/boundary data)
    - https://www.fire.ca.gov/ (CALFIRE site has some fire statistics + maps)
    - http://gsp.humboldt.edu/olm_2019/courses/GSP_216_Online/lesson6-2/metrics.html (classification metrics/terminology for maps)
    - https://github.com/giswqs (Professor that produces a lot of remote sensing guides, videos, and libraries)
    - https://github.com/giswqs/geemap (helpful library that complements EE by ^^)
    - https://callands.ucanr.edu/data.html (CA land cover aggregations by year+county)
    - https://frap.fire.ca.gov/media/10311/fveg_19_ada.pdf (CA land cover mapping)
    - https://frap.fire.ca.gov/media/10277/baileyecoregionsl3_ada.pdf (CA Level 3 ecosystems)
    - https://www.mrlc.gov/data (lots of land + vegetation cover datasets)

1) **Estimating Live Fuel Moisture from MODIS Satellite Data for Wildfire Danger Assessment in Southern California USA (2018)**
    - **Goal:** Use vegetation indices to model live fuel moisture content in Southern California to assess wildfire risk.
    - **Background**
        - Vegetation moisture is a key factor in US Forest Service NFDRS wildfire assessment
        - $LFM\ (\%) = 100 * (m_w - m_d)/m_d$
        - LFM is percent difference between wet & dry vegetation mass over dry vegetation mass
        - LFM data is usually updated every 1-2 weeks from several sample sites / most sites don't have data for more than 3 years
    - **Methods**

    - Derived NDVI and EVI from MODIS [MOD13Q1, MYD13Q1] from 10/2002 - 09/2012 as main VI
    - Also included NDWI, NDII, and VARI as other VI's indicative of vegetation water content and soil moisture
    - Fire agencies collect vegetation samples that are as representative of the region as possible, so researchers averaged VI's over 10km radius kernels since this size was the most correlated with LFM measurements
    - Pearson correlation used to select VI most correlated with LFM at different sites as the main proxy for fuel moisture. Two linear models are fit over sites with 10+ years of observations. The first only includes VI's as features and the second includes meteorological variables (temp, humidity, etc.) and VI's. Models are evaluated over 2014 Colby FIre
- **Results**
    - EVI was the most correlated VI with LFM. Benefits of applying remote sensing to LFM are that more frequent and reliable measures of wildfire risk can be produced.
- **Useful Links**
    - Data on weather/moisture/drought/fire danger

2) ~~**Combining NDVI and surface temperature for the estimation of live fuel moisture content in forest fire danger rating (2004)**~~
- **Goal:** Estimating fuel moisture content (FMC) in Mediterranean ecosystems to understand fire ignition and flammability.
- **Background**
    - Dry fuel (dead leaves, fallen branches, etc.) are much more dangerous than live fuel and are more dependent on weather conditions, so they can be modeled using atmospheric data.
    - This doesn't work as well for live fuel due to differences in vegetation types and plants adapting to overcome atmospheric changes.

3) **Observed Impacts of Anthropogenic Climate Change on Wildfire in California (2019)**
- **Goal:** Understand and measure the impact human driven climate change has had on recent wildfire seasons in California and determine whether this follows expected behavior.
- **Background**

        - Greater wildfire frequency and size has led to large increases in burned area along the West coast due to increased dry fuel content from reduced rainfall + snowpack and warmer temps, which are signs of human driven climate change
        - Could be due to increased human expansion, changes in land use/cover, and over-zealous fire suppression which leads to “fire-deficits” in some regions
        - Wildfires in the summer tend to occur in forests and wildfires in the fall occur in coastal shrubland and are caused by extreme winds.
    - **Methods**
        - Wildfire and climate data from 1972-2018 for North Coast, South Coast, Central Coast, and Sierra Nevada regions of California
    - **Results**
        - 405% increase in burned area overall. Mainly due to summer forest fires in North Coast and Central Coast regions which had 600% increase in burn areas
        - Low correlation with climate and burned areas in South + Central Coast regions due to less above-ground vegetation and most fires being started by humans.
        - Strong santa ana winds and arid conditions lead to fall fires

4) ~~Fire Mosaics in Southern California and Northern Baja California~~

5) **[Combination of Landsat and Sentinel-2 MSI data for initial assessing of burn severity]() (2018)**
    - **Goal:** Use data from Sentinel 2 and Landsat 8 to produce accurate burn severity maps.
    - **Background**
        - Landsat is traditionally used to create burn severity maps and various maps of wildfires. But Sentinel 2 has advantages including better spatial resolution and higher temporal resolution that make it more suitable for these tasks.
    - **Methods**
        - Used images for the Acebo Wildfire in Spain that is in a shrubby/forested Mediterranean climate.
        - Produce a burn severity image with only Landsat, a burn severity image with Landsat as the pre-fire conditions and Sentinel 2 as the post-fire conditions, and compare the accuracy of both to a high resolution image from Pleiades 1 B.

- **Results**
    - Errors are more prevalent in unburned / low severity regions.
    - Using only Landsat images has higher accuracy, but in the case where a post-fire Landsat image is unavailable there is only a minor accuracy decrease with a Sentinel image.

6) **Mapping Fire-Induced Vegetation Mortality Using Landsat Thematic Mapper Data: A Comparison of Linear Transformation Techniques (1998)**
    - **Goal:** Compare two linear transformation methods: Kauth-Thomas / Tasseled Cap (KT) and Principal Components (PC) and evaluate their effectiveness at mapping fire severity.
    - **Background**
        - Fire severity maps generated from remote-sensed data are faster and cheaper than manual field surveys.
        - Changes in vegetation and soil from a fire are detectable if forest canopy density is not too high and the fire doesn't consume only litter.
        - KT transform has varying coefficients depending on which Landsat data is used
        - PC transform compresses data such that a few principal components contains a majority of the variance in data
    - **Methods**
        - Transforms are applied to Landsat images over the 1994 Rattlesnake Fire in southeast Arizona
        - Image compensated for atmospheric path radiance with an iterative band ratioing procedure, which requires no extra data compared to dark body subtraction and empirical line-method.
        - 500 points in the fire area were sampled to determine vegetation mortality
        - US Forest Service defined burn severity classifications are used
        - Apply derived KT coefficients to Landsat bands and take the first three KT features: brightness, greenness, wetness
        - Compute PC components from image and take the first three which hold 98% total variance
        - Apply Gaussian stretch to both KT, PC features to increase contrast
        - Fit minimum distance classifier to 50 labeled training points
    - **Results**
        - KT transform performed better with a kappa of 0.73 compared to PC transform with a kappa of 0.62

        - KT transform had high commission/omission errors for Class 3 (USFS class 4)
        - KT and PC features 1,2 are very similar, but for feature 3 (wetness) PC is not as accurate
        - Both perform well at classifying Class 1,2 burn severity

7) Classifying and Mapping Wildfire Severity (2005)

- **Goal:** Compare 6 different methods of classifying burn severity using Landsat data. The methods include: temporal image differencing and ratioing, principal component analysis, and artificial neural networks.
- **Background**
    - Wildfire burn severity maps are important for many reasons: they record the effects of a fire, help agencies plan and monitor forest recovery, can be used to update vegetation maps, provide baseline data for future analyses, and guide future policies and management.
    - Traditional methods of producing maps involve field surveys, manual interpretation, in-situ sampling, and aerial imagery but these methods are inconsistent, time-consuming, not easily scalable to large regions, and don't include infrared/microwave bands that are relevant to vegetation.
    - Lots of research on vegetation change detection with remote sensing and these methods can be grouped as visual change detection (on-screen digitizing), multiple classification comparison (pre-post comparison), image algebra (indices + ratios), and multi-temporal composite classification.
- **Methods**
    - Region of interest is Fort Howes wildfire complex in Custer National Park in Montana
    - 268 sites were selected and divided into train (n=196) and test (n=72) sets
    - Sites were labeled by the USFS using a mix of aerial+ground images and Landsat data
    - Processing images for differencing methods involves using VI,
    - **Image Differencing**
        - Use normalized burn ratio and a slightly modified version as VI's of interest
        - VI's were calculated pre + post fire and each pixel is labeled by vegetation type (tree, shrub, grass) using USGS NLCD data.
        - Pre + Post fire images are differenced and burn severity thresholds are established and applied for each vegetation type
    - **Principal Components**

            - Combine all bands from pre/post images in PCA and visually identify the two most associated with burned areas
            - Use spectral scattergram to identify burn threshold and create burn index for every pixel based on vegetation type
        - **Neural Networks**
            - Artificial neural networks with back-prop/k-nn as inductive learning algorithms
            - Different from traditional classification methods that use spectral data because labels account for nearby pixels
            - For single image post-fire analysis all bands are used
            - For pre-post analysis, all bands from the pre image and an additional NDVI are used along with 4 bands from the post-image
    - **Results**
        - All methods classified total burned/unburned areas similarly
        - Mapped ANN results were more "blocky" since it accounts for neighboring pixels during classification
        - User accuracies (precision) are 100% for all methods for burned land
        - User accuracies for unburned land are around 90% for all methods except for their second image differencing method which is 68%
        - Producer accuracy (recall) is 100% for all methods for unburned land
        - Producer accuracy is around 90% for all methods except ND4/5 for burned land
        - Overall accuracy for burned/unburned land is around 95% for all except ND4/5
        - Accounting for vegetation types accuracy ranges from 72%-96%
    - **Useful links**
        - http://gsp.humboldt.edu/olm_2019/courses/GSP_216_Online/lesson6-2/metrics.html

8) **Sensitivity of X-, C-, and L-Band SAR Backscatter toBurn Severity in Mediterranean Pine Forests (2010)**
    - **Goal:** Compare performance and behavior of SAR X/C/L bands when used to study fire burn severity in Mediterranean ecosystem forests in Spain
    - **Background**
        - Most common burn severity techniques is using NBR and differencing pre-post fire images with SR data
        - Standard index-based remote sensing methods rely on indirect measures of burned areas eg: nir decrease with decrease in green vegetation but this

behavior is inconsistent with intermediate burn levels where multiple things occur eg: litter is burned and soil is slightly charred
    - Using SAR data can provide information on biomass and vegetation structure. Higher frequency bands have less penetrating power and are blocked by tree canopies
    - Observed behavior of SAR bands are strongly dependent on a region's land cover, vegetation type, topography, and weather.
    - AOI is three separate wildfires in Spain in a region with hilly terrain and a Mediterranean ecosystem
    - Landsat images were used as a baseline comparison
    - in-situ precipitation and temperature samples are used
- **Methods**
    - Analyses are focused on Zuera08 fire, Jaulin09 fire was used to confirm results, and Zuera95 fire was used to analyze the effect environmental conditions have on C-band
    - Descriptive statistics used to analyze backscatter as a function of burn severity
- **Results**
    - For X/C bands HH copolarized backscatter increased with burn severity. This trend is much stronger when the angle of slopes faced the sensor
    - L band HH polarized backscatter decreased with burn severity. L band is less affected by absorption/attenuation, scattering from the surface doesn't have a big impact. So canopy vegetation makeup most of the backscatter, but with higher burn severity there is less tree canopy.
    - For unburned regions backscatter increases with local incidence angle. For highly burned regions copolarized backscatter HV increases with LIA but decreases for polarized backscatter due to sensitivity to ground scattering at steep angles
    - Wet conditions increase sensitivity of copolarized waves to burned areas
    - Local incidence angle strongly affects backscatter for all SAR bands and wave polarizations

9) [Estimation of Forest Fuel Load From Radar Remote Sensing](#) (1999)
- **Goal:** Use SAR to accurately map forest biomass/fuel loads
- **Background**
    - Fuel load maps are used to understand fire behavior and plan for fire management

- Wildfire simulations require maps of fuel loads, which are estimated from species based algorithms or samples. SR data collected from passive sensors are shown to be effective at mapping burn severity, area, etc.
- Canopy fuel characteristics that are most important for predicting fire risk/ behavior cannot be easily derived from passive optical sensors. Active sensors can be used to estimate canopy height, water content, biomass, etc
- Radar at low frequencies (400-1500 MHz) is sensitive to crown/stem biomass and moisture content
- Radar is not affected by light, smoke, and clouds
- Two main types of fires are surface & crown fires. Surface fires involves fuel on the surface and crown fires involve tree canopies. Surface fires can be harder to study with remote sensing due to canopy cover
- Backscatter at linear polarizations is sensitive to forest structure and biomass
- Strong backscatter above noise level is from objects with moisture content
- Statistical approach for estimation involves correlation between backscatter and forest structure from field data
- Estimation of forest parameters from physically based models requires inversion techniques like semiempirical / parametric approach or neural networks
- Polarimetric radar backscattering provides independent measurements of biomass and structure
- Backscatter can vary for forests with similar biomass due to differences in canopy architecture, moisture, soil composition, etc.

- **Methods**
    - Area of interest is Yellowstone (YNP) because it contains vegetation common to the Northern Rocky Mountains and has a large collection of images, remote sensed data, GIS, etc.
    - Field data collected from 833 plots in 64 vegetated stands included: habitat type, canopy cover, average shrub height, etc.
    - SAR data collected from NASA AIRSAR in P/L/C bands and resampled to 10m spatial resolution. C band is used to infer topography
    - Canopy fire fuel parameters of interest are canopy fuel weight/biomass, crown bulk density, and foliage biomass
    - Calculate crown and stem biomass by fitting models to training set of plots and compare correlation with predicted and measured values of biomass
    - Second order polynomial regression used for sample plots and linear regression for stand plots with above-ground biomass as the input variable to model backscatter
- **Results**

- **Above-ground Biomass**
    - Stand level models had significantly higher R^2 for both P/L band backscatter due to having more pixels and less influence from speckling and misregistration errors
    - Plot and stand level models are more sensitive to biomass from P-band data
    - L band backscatter is more sensitive to plots with low biomass
    - Including plots with a more diverse range of biomasses can improve correlation between backscatter and biomass
- **Crown Biomass**
    - R^2 of predicted and measured biomass for both P/L bands are 0.55, 0.54
    - For L-band backscatter, there is strong correlation at low biomass and no correlation at high biomass. This is expected since the L-band signal weakens with greater tree canopy densities, which reduces its sensitivity in high biomass crowns
    - Since P-band has greater penetration than L-band, in low biomass crowns the signal penetrates the canopy and hits the soil surface, which produces a lot of backscatter and leads to overestimates of biomass
    - Fitting an equation with both L/P-band cross polarized backscatter addresses the issues with using them individually and has R^2 of 0.73
- **Stem Biomass**
    - R^2 of field measured and predicted stem biomass is 0.81 for P-band and 0.57 for L-band
    - P-band performs better since it has greater canopy penetration and its signal is not backscattered by leaves as much compared to L-band
    - P/L-bands stop being accurate at biomass of 200Mg/ha and 100Mg/ha where the backscatter is less sensitive
    - Biomass prediction is worse for plots at high elevation/steep slopes
    - Performance does not improve from combining both bands
- **Spatial Distribution of Stem/Crown Biomass**
    - Maps with traditional biomass classifications were produced by creating class thresholds for estimated biomass and classification accuracies are 84% for crown biomass and 86% for stem biomass

- Both P/L-band SAR can be used to predict canopy fuel parameters accurately for forest and fire management applications

    - P-band is more suited for old-growth forests with denser canopies and fuel loads
    - L-band is more suited for surface fires and low density forests
    - Crown biomass and height are the most important features for estimating canopy fuel loads

~~10) Burned area detection and mapping using Sentinel-1 backscatter coefficient and thermal anomalies (2019)~~

- **Goal:**
- **Background**
- **Methods**
- **Results**

11) Random forest classifier for remote sensing classification (2005)

- **Goal:** Compare model performance, runtime, and usability of random forest and support vector classifiers using Landsat images to classify land cover
- **Background**
    - Ensemble classifiers perform better than their individual classifiers
    - Using boosted decision trees has led to significant increases in accuracy for land cover classification studies
- **Methods**
    - Area of interest is agricultural region near Cambridgeshire, UK
    - Land cover classes: wheat, onion, peas, lettuce, bean, potato, and beet
    - Different #'s of features and trees tested for random forest and optimal number is 3 features and 100 trees
    -
    - **Random Forest**
        - Consists of many distinct decision tree classifiers that each cast an unweighted "vote" to classify a pixel
        - Bagging is a method to create training sets by sampling with replacement N observations and training each weak learner on this data
        - Gini Index is used as feature selection metric
        - Overfitting is not an issue and trees are not pruned in random forest since studies suggest that as the number of trees increase, generalization error always converges with or without pruning from Strong Law of Large Numbers
    - **SVM**

        - Aim of determining decision boundaries that optimally separate classes by maximizing their margin and minimizing misclassification
        - SVM with regularization C=5000 and a radial basis kernel with a width y=2 are used. 1v1 used for multiclass problem
- **Results**
    - Optimal number of trees were tested from 100-12000 and the test accuracy ranged from 88% - 88.4%. This shows that pruning for overfitting is not necessary
    - Precision of random forest and svm is lowest for lettuce, beets, and onions.
    - Overall accuracy of random forest and svm is 88.4% and 87.9%
    - Training runtime of random forests is 5 seconds faster compared to svm
    - Random forests requires only two simple parameters (# of features/trees) to be set compared to svm (kernel, kernel parameters, regularization)
    - Categorical features, unbalanced data, and missing values can be handled by random forests, unlike svm
    - Indirect feature selection can be achieved with the features used in trees

12) **Near Real-Time Wildfire Progression Monitoring with Sentinel-1 SAR Time Series and Deep Learning (2020)**
- **Goal:** Apply CNN and deep learning techniques to SAR images to detect changes in burned areas quickly
- **Background**
    - Main advantage of SAR is that it works day/night and can penetrate clouds, smoke, ash, and other atmospheric conditions caused by fires that severely limit the use of normal optical sensors
    - SAR signals can penetrate and provide data on the physical structure/characteristics of vegetation, tree canopies, and soil (varies by SAR band type)
    - Current methods of wildfire monitoring use data from MODIS, VIIRS, LANDSAT, and Sentinel-2 to conduct post-fire analysis and mapping
    - SAR data is challenging to use in analyses since there are many highly complex parameters that affect backscatter including: soil moisture, incidence angle, surface terrain, topography, polarization, speckling, band penetration, etc.
    - Deep learning can be effective for change detection since it learns complex relationships between features
    - Areas of interest are Elephant Hill, Camp, and Chuckegg Creek fires located in British Columbia, Northern California, and Alberta
- **Methods**

- C-band SAR data used from Sentinel-1. Data is in VV + HV polarizations, terrain corrected, and converted to decibel with log scaling
- Sentinel-2 SR data used to verify results of SAR analysis by calculating burned areas using dNBR
- Precipitation data is used to account for weather conditions that could affect SAR backscatter
- Several AOI's for each fire were selected to understand temporal backscatter patterns in burnt/unburnt and forested/grassy regions
- **Neural Network**
    - Log ratio is calculated for pre/post fire images to map changes caused by wildfire
    - Binary map of burnt/unburnt areas is created using time series anomaly detection method
    - Training samples are automatically generated from binary map and a CNN is fitted to generate burn confidence map
    - Burn confidence map is binarized using Otsu automatic thresholding method
    - Individual fire progression maps are merged to improve reliability and consistency
    - CNN is designed with 18 layers, learning rate of 0.0001, and ADAM optimizer

- **Results**
    - In AOI's of the Elephant Fire, the VV, VH polarizations for forests and grasslands had significant changes in burned regions. For the Camp Fire, precipitation after the fire begins leads to an increase in backscatter instead of a decrease for both burnt and unburnt regions
    - In the Camp Fire VH is more sensitive than VV to changes caused by fire
    - CNN approach performs better the log-ratio kmap at detecting burned areas

13) [Remote sensing techniques to assess active fire characteristics and post-fire effects](#) (2005)

- **Goal:**
- **Background**
- **Methods**
- **Results**

14) **[Implementation of machine-learning classification in remote sensing: an applied review](#) (2017)**

- **Goal:** Demonstrate potential of different machine learning classifiers in remote sensing applications and compare their performance and usability to more traditional methods
- **Background**
    - Use of ml is increasing in remote sensing due to its ability to model complex relations and work with high dimensional data
    - Studies have shown that it tends to outperform traditional parametric classification methods
    - Traditional methods are still very popular due to lack of support of ml in software and confusion on how to use ml
    - Lots of previous research has presented contradictory results on model performance likely due to different data characteristics, methods of parameter tuning, class imbalance, etc
    - Ensemble methods are shown to outperform single classifiers
    - Past research indicates random forest performance is not affected by the number of trees and only suffers a minor decrease in accuracy based on the number of nodes
    - Focus is on SVM, decision trees, random forests, boosted trees, artificial neural networks, and k-NN
- **Methods**
    - Two data sets used, Indian Pines AVIRIS + GEOBIA Land Cover
    - All features are normalized, feature selection is done with random forests, and under-represented classes are balanced using random oversampling
    - 10-fold cross validation used to tune model parameters
    -
- **Results**

15) **Next Day Wildfire Spread: A Machine Learning Data Set to Predict Wildfire Spreading from Remote-Sensing Data (2021)**

16) **Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR) (2006)**

- **Goal:** Develop a relative burn severity index that is uncorrelated with pre-fire vegetation cover in order to reduce misclassification in low vegetated pixels or pixels with varied vegetation. This would be widely generalizable to wildfires in Northern California and allow for better comparison with different wildfires

- **Background**
    - Change detection with remotely sensed data usually occurs by differencing indices derived from pre-post fire images
    - Method of absolute differencing can lead to misclassification in low vegetated pixels or pixels with different vegetation types
    - A common problem with mapping moderate/high burn severity is inconsistent behavior of indices due to differing amounts of pre-fire cover eg: Given two pixels that have low and high amounts of vegetation and they both burn completely, they should both be classified as high severity burn regardless of the amount of vegetation burned
    - Techniques using multiple images (PCA, aNN) can account for pre-disturbance conditions, but can be difficult to apply
    - Burn severity is roughly defined as the effect of fire on an ecosystem and this is affected by the region's ecosystem, terrain, vegetation cover, etc.
    - NBR ranges from [-1, 1] but is traditionally scaled by 1000 to transform it to integer format
    - Collected field data (CBI) is uncorrelated to the amount of pre-fire vegetation cover (NBR)
- **Methods**
    - Landsat images and data from 14 fires in Sierra Nevada analyzed / Fires cover a variety of different elevations, sizes, vegetation types, and ecosystems
    - Field data for burn severity recorded at each fire using Composite Burn Index (CBI) / vegetation chunked into 5 groups and assessed separately using several measurements (eg: % canopy mortality, soil color) to classify burn severity
    - Images are selected to minimize difference between fire start/end dates to minimize seasonality in ecosystem + changes in lighting and corrected for terrain
    - Calculate NBR of pre & post images, multiply by 1000, difference pre + post fire images to get dNBR, average pixel values in 3x3 window to match 90m diameter of in-situ sample sites, and normalize dNBR by subtracting the mean dNBR value of an unburned sample site beyond fire perimeter
    - $RdNBR = \frac{(PreFireNBR - PostFireNBR)}{\sqrt{abs(PreFireNbr/1000)}} = \frac{dNBR}{\sqrt{abs(PreFireNbr/1000)}}$
    - Non-linear regression analysis is performed to examine whether RdNBR or dNBR is more related to in-situ measurements (CBI)
    - Burn severity thresholds are produced for RdNBR / dNBR and compared
- **Results**

- dNBR is correlated with the amount of pre-fire vegetation and provides a measure of how much vegetation is killed
- RdNBR measures the amount of vegetation killed in relative to the amount of pre-fire vegetation
- Positive values of RdNBR+dNBR represent a decrease in vegetation cover & vice versa
- Results of regression analysis show that RdNBR ($R^2 = 0.61$) is more correlated with CBI than dNBR ($R^2 = 0.49$) and residuals of RdNBR are less heteroskedastic, especially at low-moderate RdNBR values
- Overall accuracy and kappa is similar but RdNBR has better recall and precision scores for areas with high burn severity + lower recall for unburnt and low severity burn areas compared to dNBR
- Using a relative change index (RdNBR) for fires can be more appropriate than an absolute change index (dNBR) for applications that define burn severity by a fire's effect on vegetation
- A relative index allows for a more consistent definition of severity for different fires and improves accuracy for high burn severity pixels in heterogeneous ecosystems
- In homogenous ecosystems, thresholds based relative and absolute indices should perform similarly

15) [Review Article Digital change detection techniques using remotely-sensed data]() (1989)

- **Goal:** Compare how different methods of change detection using remote sensing data lead to different results, even in the same environment
- **Background**
    -
- **Methods**
    -
- **Results**

16) [Calibration and validation of the relative differenced Normalized Burn Ratio (RdNBR) to three measures of fire severity in the Sierra Nevada and Klamath Mountains, California, USA]() (2009)