Slide 1 – Title Slide

Hello and welcome to Week 2, Part 4 of EGM703: Applications of Hyperspectral Remote Sensing.

Slide 2 – (Some) hyperspectral applications

In this lesson, we'll look at some different applications of hyperspectral images – as always, there are many, many more applications than what we cover here, but I've tried to put together a nice collection of different topics and studies. We'll start by looking at mineral exploration and mapping, before looking at a few examples of vegetation studies, and then finish up by looking at some examples mapping oil spills.

Slide 3 – Mineral exploration

Mineral exploration, or looking for evidence of particular minerals underneath the ground, is a big part of the mining process. As we have discussed previously, different mineral types can be identified using different portions of the electromagnetic spectrum. For iron-rich minerals, the visible and near infrared portion of the electromagnetic spectrum is quite useful. Here, we have spectral signatures for some iron-rich minerals such as Jarosite, Hematite, and Goethite – you can see that they are quite varied at visible and near-infrared wavelengths, so we can use these wavelengths to help identify these different minerals. For clays, micas, and sulfates, the shortwave infrared portion of the spectrum, between about 2000 and 2500 nanometers, is the most effective. The plot here shows a number of mineral signatures in the shortwave infrared, and you can see a number of different absorption features that make it possible to differentiate between them. Note that these signatures are offset, in order to more easily compare them. Finally, silicates and carbonates are often easily distinguished using the longwave, or thermal, infrared that we covered last week. As you might have guessed, hyperspectral images can be used to identify both minerals and mixtures of minerals – we've seen some examples of this when we talked about cross-correlogram spectral matching – this example here shows an example of a spectral signature of a mixture of minerals, with the different absorption features labeled with which mineral causes them. Like with other remote sensing applications, we can more easily map large areas using hyperspectral images than we can with field-based studies, though field-based studies are still important because (a) it's always good to check remotely-sensed observations on the ground, and (b) who doesn't love playing outside? The last image I'll put up here shows how we can use a digital elevation model in conjunction with a classified image, in order to help us visualize the field conditions and intuit the geological relationships between the different features that we've mapped. These images all come from this paper, Kruse 2012; another good review paper for mineral exploration and remote sensing is by van der Meer and others, also from 2012 – I included this paper in the Week 1 library, but it's also in the Week 2 list for you.

Slide 4 – Vegetation health

Another important application of hyperspectral remote sensing, and of remote sensing more generally, is in monitoring crop and vegetation health. Changes in vegetation health lead to changes in reflectance spectra for plants – for example, we have a number of different spectral signatures here showing different stages of health and disease for tomato plants, taken from this 2003 paper by Zhang and others. The curve marked 'H' here shows the reflectance for a healthy tomato plant, while the curves marked 1-4 show the reflectance for tomato plants at different stages of late blight disease, an infection that can have devastating effects on both tomato and potato crops. The curve marked 'S' here shows the average reflectance curve for the soil in the study area. This study used an AVIRIS image – remember that this is a sensor with 224 spectral bands - to work on identifying these different stages of disease in tomato crops. They used the minimum noise fraction to reduce the 224 bands to reduce the dataset and focus on the bands that contained the most information. Using spectral angle mapping with field-measured reflectance spectra, they were able to identify tomato crops with different stages of late blight disease, using only the hyperspectral image. The image on the left here shows a false-color composite image of the field, while the image on the right shows the same field with the different stages of disease identified. This kind of application is a pretty important one for monitoring crop health and identifying potentially devastating crop diseases early, so that they can be addressed before they become disastrous.

Slide 5 – Species identification

Another application that we've seen before is using hyperspectral imagery to identify, or classify, different species of plants. In a review paper published in 2016, Fassnacht and others looked at how hyperspectral remote sensing has been used to study tree classification. As we saw with studies of urban heat islands, there's been a huge growth in the number of studies published that address tree species classification, driven in part by a large increase in the number of studies using hyperspectral data. They also summarized 13 studies, looking at the different spectral bands and methods used. They found that most (12 of the 13) studies used the region around 650 nanometers, corresponding to visible red light. Outside of that region, there was significantly more variety – we can see here a number of studies that used other visible wavelengths, though not all; a number of studies that used wavelengths around 1100-1200 nm in the near infrared, and even all the way out to the shortwave infrared – in all, most of the visible, near infrared, and shortwave infrared regiosn are used in at least 1-2 studies. Like we've seen previously, the particular selection of wavelengths is going to depend on the specific species being studied, and the relevant absorption features in their spectral signatures – there's not really a "one size fits all" approach to be found.

Slide 6 – LiDAR Fusion

We can also combine hyperspectral images with other data sources, to gain the unique advantages offered by each. We've seen how hyperspectral data contains lots of information about reflectance spectra of different surfaces; in EGM702, we discussed how LiDAR provides estimates of height, but also vegetation structure more generally. So, if we were to combine hyperspectral data with LiDAR data, we might be able to get the best of both of these worlds. This is especially true in studies of tree species identification in 'complex' forests, where we have many different species that have similar spectral properties, but different physical properties or heights, and vice-versa. This study from 2008 by Dalponte and others used LiDAR data, along with an airborne hyperspectral camera, to classify tree species using a support vector machine classifier. The results they obtained were highly accurate, though using LiDAR returns beyond the first return (in other words, information about the canopy structure) did not significantly improve the results. On the whole, however, this sort of hyperspectral/LiDAR fusion produces very good results.

Slide 7 – Oil spill detection

The final application we'll cover this week is oil spill detection. As you are hopefully aware, oil can have serious impacts on marine environments. These impacts are no limited to the big attention-grabbing spills like the 2010 Deepwater Horizon disaster in the Gulf of Mexico – smaller leaks or spills can also be damaging, and happen more frequently. The plots shown here, from a 2013 paper by Lu and others, shows how a very thin film of oil, also known as a slick, can change the reflectance curve of seawater. These don't even have to be thick films – even a film as thin as 1.2 microns produces a measurable change in the reflectance curve. This change is something that we can detect using hyperspectral imaging. While it can be difficult to measure the thickness of the slick using optical data alone, detecting the presence of oil using hyperspectral images is an easier problem to solve. This image here, from a 2005 study by Salem and others, shows the distribution of oiled water in a watershed in Maryland, identified using a hyperspectral image and maximum likelihood classification. The thing to remember here is that these are not the result of large, catastrophic spills, but they instead show how prevalent oil can be as a result of small spills or leaks.

Slide 8 – Summary

In this lesson, we've looked at a few different applications of hyperspectral remote sensing. As we've seen, there are a number of different applications across a number of different fields of study. We've also seen how many of these studies combine methods we've seen in other modules with hyperspectral-specific methods; for example, SVM and maxmimum likelihood classifiers alongside Minimum Noise Fraction reduction. We've also seen how fusion with other data sources, such as LiDAR, can be especially powerful, especially for tree species identification.

Slide 9 – Additional resources

As always, I've included links to the different articles referenced in this presentation here – they're also available on the slide notes, and you can find PDF versions of the articles on Blackboard or in the Zotero library. I've also added a few additional papers to the Zotero library that weren't covered here, so feel free to browse those as well. That's all for this lesson – I hope you found it interesting, and you have any questions, please don't hesitate to e-mail me or post in the discussion forum on blackboard. Bye!