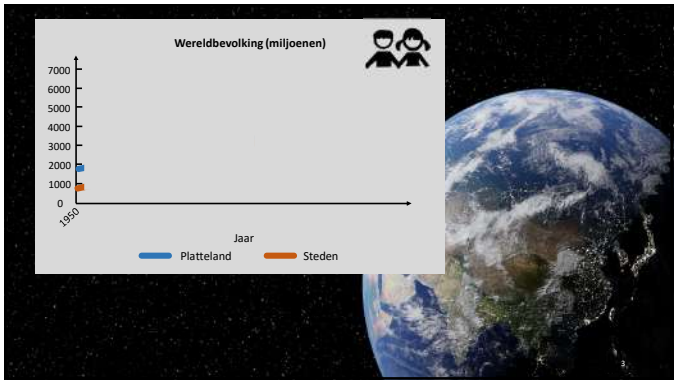
Welcome to my public defense, entitled:

Mapping urban composition and green infrastructure using remote sensing in support of urban ecosystem service assessment

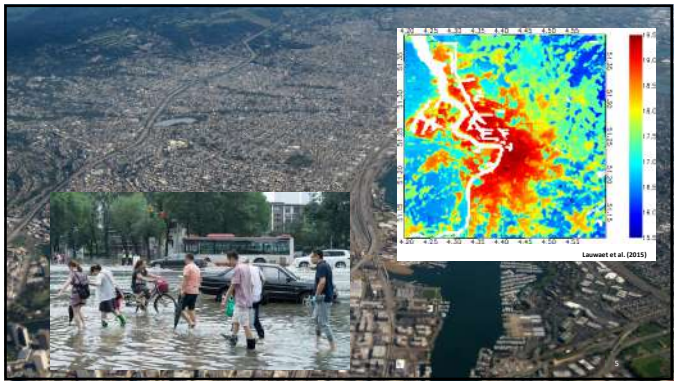
Hard to guess from the title, but actually a large part of my PhD was about cocktails...



We all know global human population is rising, but there's also a big change in WHERE we live: people are more and more moving into cities.

We choose to live in cities due to economic and social benefits (easy access to jobs, goods, services...).

Cities are true hotspots of environmental pollution and CO2 emissions, in turn affecting our health on a local scale and climate patterns on a global scale.



Two well-known effects of global climate change are an increased occurence of heat waves and heavy rainfall events.

As cities mainly consist of concrete, they are most vulnerable to these effects.

Urban planners face the challenging task of designing our cities in such a way to ensure they have a low impact on the surrounding area and are prepared to face the consequences of climate change.

Urban green is definitely part of the solution here, as plants produce many so-called ecosystem services which both help in reducing our emissions and making our cities more resilient against climage change.

Many different types of urban green exist, each with their own specific set of benefits.

The question now remains: where do they have to plant which type of green in order to have maximum impact?

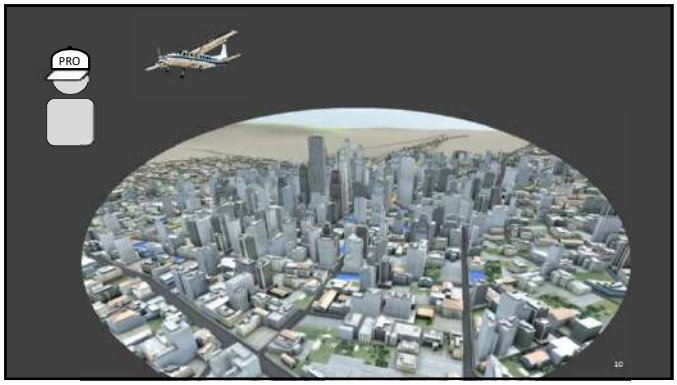
Ideally, they could start their assessment based on ecosystem service maps (right). These maps would help them to locate areas in the city where there's a shortage of a certain service --> they then know where to focus their efforts.

These ecosystem service maps are created by urban modellers, and they require quite some input data concerning the composition of the city.

1. They need to know WHERE the urban green is located (so need to distinguish green from non-green elements).
2. They need to know WHICH TYPE of green there currently is.
3. They need to know the properties of the urban green (for instance, unhealthy trees won't produce that many ecosystem services)

So we know what we want to do, the remainder of the presentation will be about the HOW

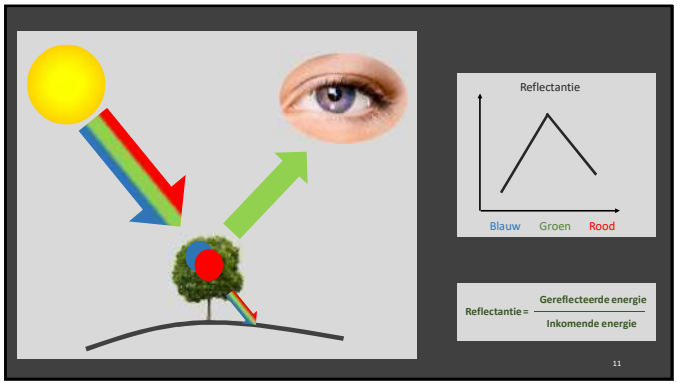
-> we will use remote sensing.



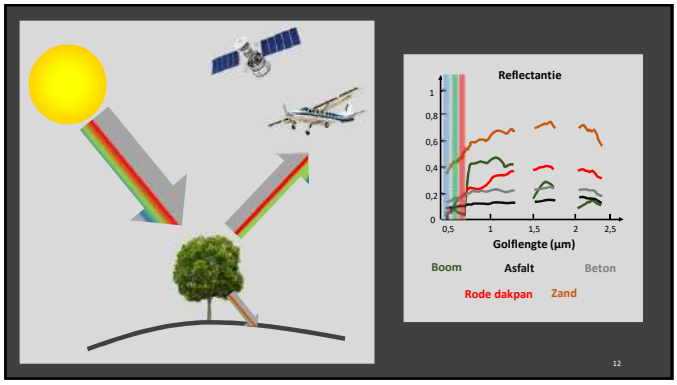
Why remote sensing? It simply allows us to acquire objective information about our city in one go, whereas the traditional approach (field work) resulted in fragmented information.

So we put a camera in an airplane and fly over the city.

But how do we extract the information we need from the images?

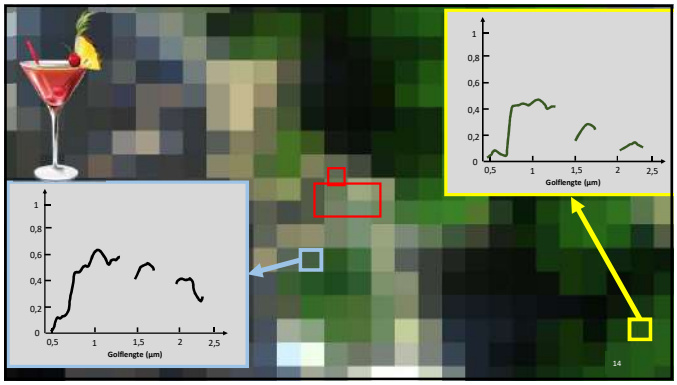


Our eyes are cameras as well. The sun emits radiation in different colors (our eye is sensitive to blue, green and red). The radiation gets transmitted, absorbed or reflected by objects. In case of trees, mainly the green light is reflected and that's why we see trees as green. Ratio of reflected versus incoming radiation is called reflectance and we can plot it in reflectance curves.

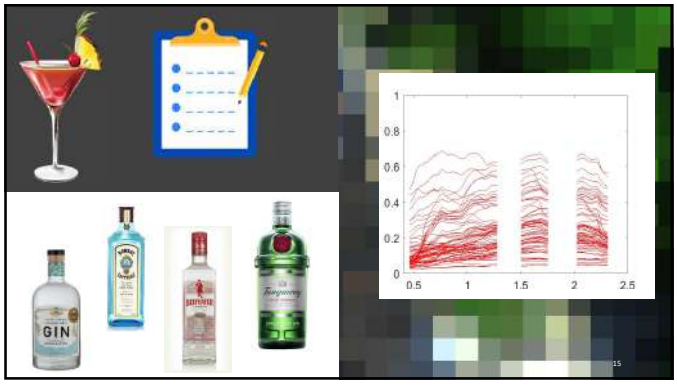


Actually the sun emits radiation in many more colors, not visible to our eye. We can however build cameras that can capture this radiation... As each type of object interacts differently with solar radiation, the shape of the curves can be used to differentiate between objects. This is the basis for mapping based on remote sensing data.

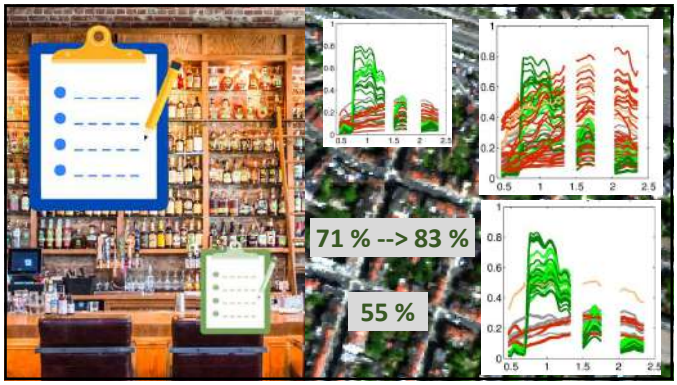
Let's move to the first part where we are trying to distinguish urban green from non-green elements in the city.



We flew over Brussels using this special camera. At first sight it's very easy to distinguish green from non-green. We want to have a detailed map however and as we zoom in, we notice that the image consists of pixels and some of these pixels actually contain a mixture of multiple objects --> such pixels can be compared to a cocktail!



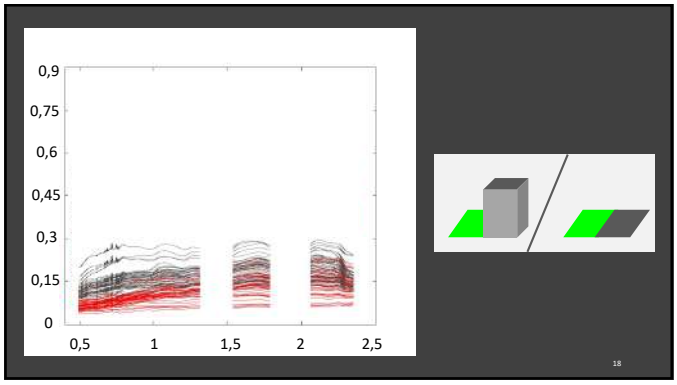
Imagine you are offered a 'secret' cocktail and you want to know what's in there and in which quantities. The list of possible ingredients is endless because of all the variations of the same ingredient (different types of gin). In remote sensing, we face the same problem, as the signal of a roof for instance greatly varies depending on its properties. So we first need to limit this ingredient list in some way before we get started. Traditionally, people just randomly deleted some types of gin in order to keep things manageable, but that's not what I did...



Instead, I walk up to the bar and check out what's available there in order to get an idea of what could possibly be in that cocktail and I use that information to reduce the ingredient list. Similarly, I look to the broader context of that mixed pixel and reduce the ingredient list so that it only contains the most relevant ingredients.

This step resulted in an average increase in final mapping accuracy from 71% to 83% and I got to this result by only using 55% of the ingredients compared to the traditional approach.

Now how do we know what's ACTUALLY in this cocktail? We make a cocktail using each combination of ingredients on our reduced list and check whether the color matches the color of the secret cocktail. BUT if your ingredients are somewhat similar, you might get the same result with a different set of ingredients...

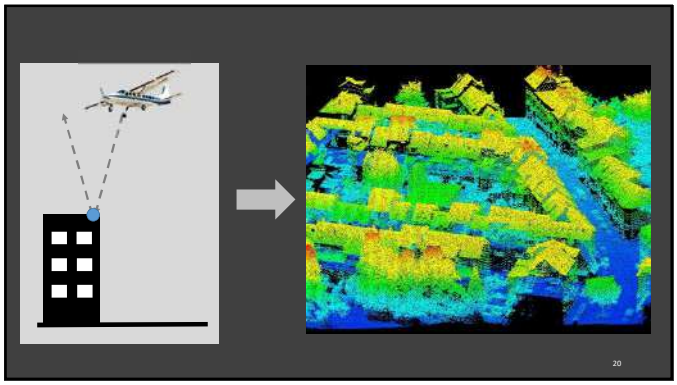


Similarly, in remote sensing, different materials look very much alike (for instance bitumen roofs and asphalt), in turn leading to confusion between mixtures of for instance grass + roof and grass + asphalt...

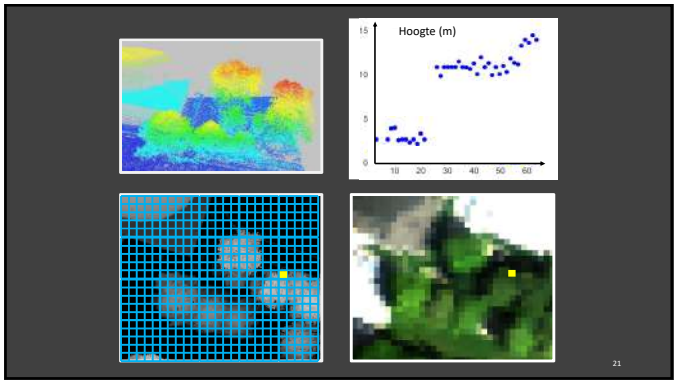
How do we solve this problem?

We TASTE!

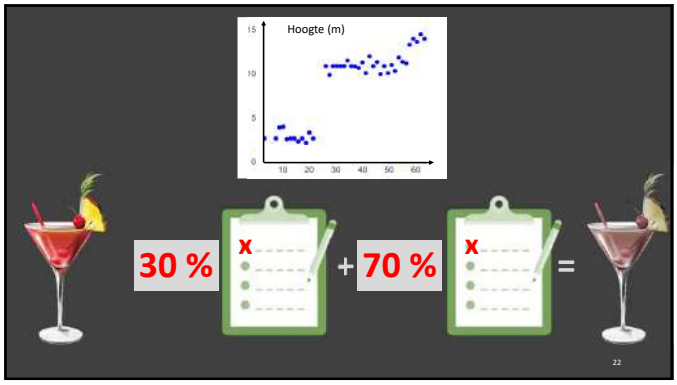
We are using other, additional criteria to evaluate the different cocktails and compare them with the secret cocktail.



We retrieved this extra information from LiDAR data, which is another remote sensing technology, which emits millions of laser pulses and measures the time for the laser to get back to the airplane. This procedure results in a very detailed 3D model of our city.



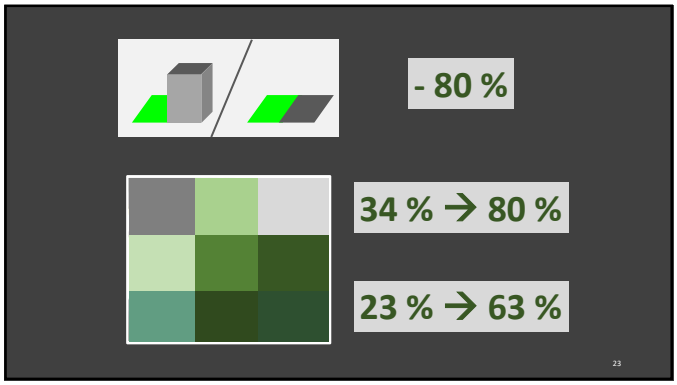
From this 3D model, we extract the HEIGHT of objects. Since this height data is much more detailed compared to our spectral information, we now have for each pixel a series of different height values.



We use this information in two ways:

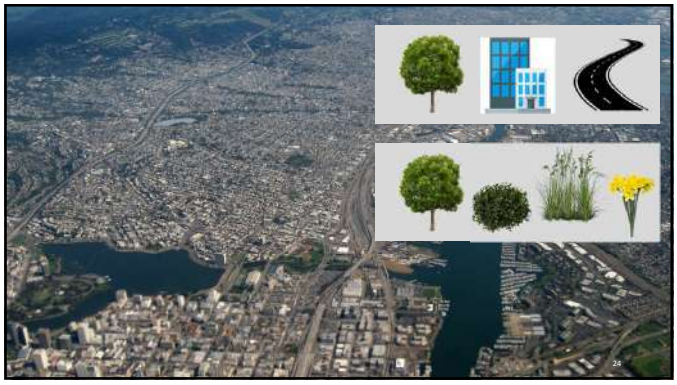
1. to eliminate certain things from our ingredient list (for instance if all height values are above 2m, you can eliminate all low objects like streets and grass).

2. We use it to set the ratio of ingredients in the cocktail.



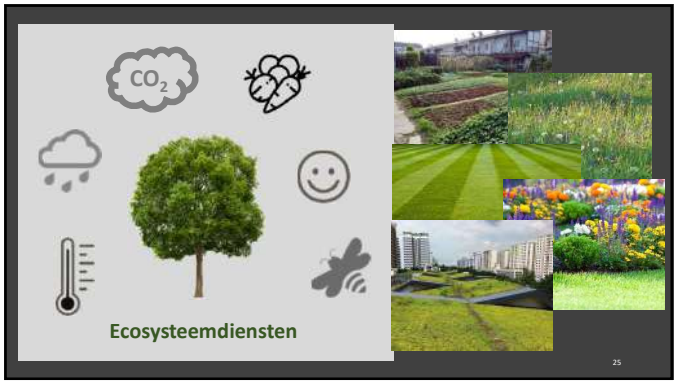
Using this technique, we were able to lower the confusion between for instance grass+building and grass+road by 80%. The accuracy of the unmixing algorithm also increased from 34% to 80%.

Additional tests on lower resolution data (Sentinel-2) were also quite successful: accuracies increased from 23% tot 63%

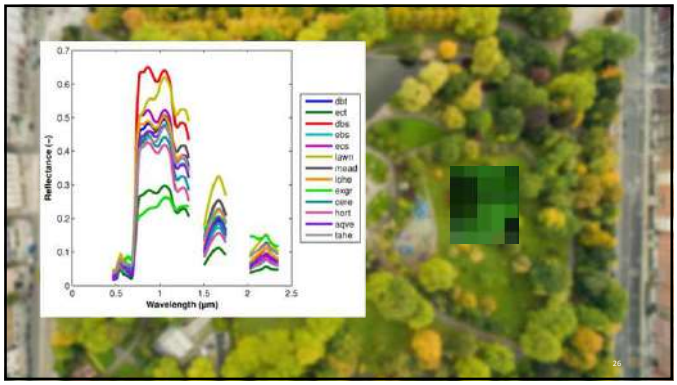


This concludes the first part.

Now we want to distinguish different types of green.



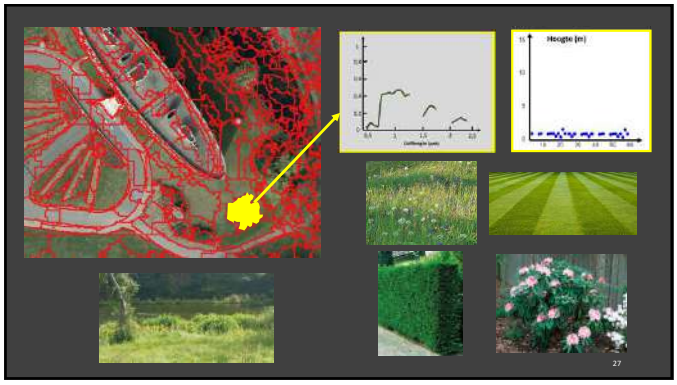
Recall that different types of green produce different ecosystem services, so we want to distinguish between agriculture, flower meadows, flower beds, lawns and green roofs for instance.



Sadly enough, these green types always occur in a very intimate mixture with one another and additionally, they are spectrally very similar.

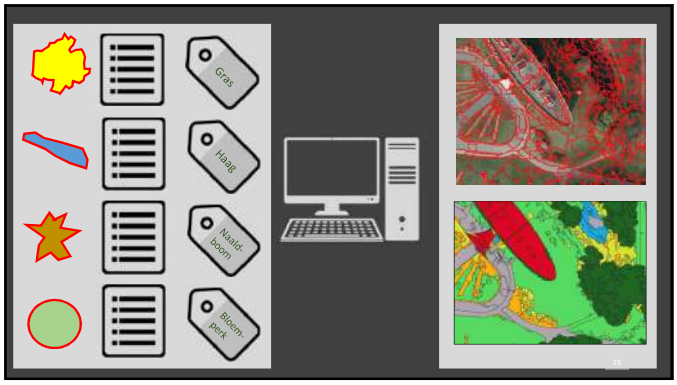
So again we need more information. Height would be useful but not always, as flower meadows and low shrubs for instance all have similar height values.

We will be moving from the pixel level to the object level to reveal even more information...



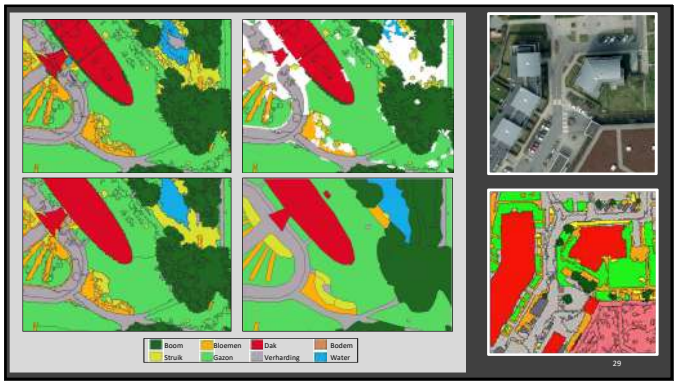
We create objects based on our pixels by grouping pixels that have similar properties together.

This way, we not only have an average spectral signal and a series of height values, but also information on the VARIABILITY within an objects, about its SHAPE and about its CONTEXT (for instance to detect waterplants next to water...)

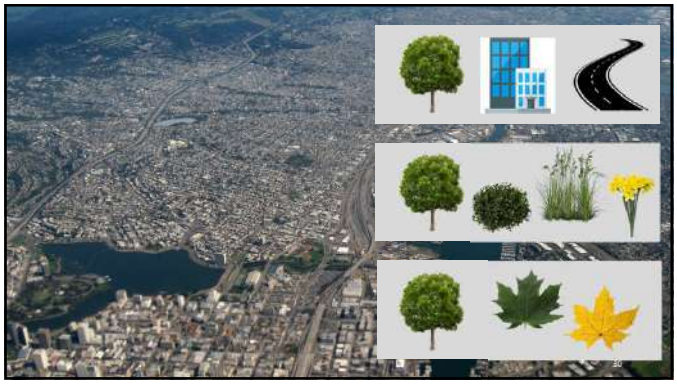


So we gather a series of objects with their properties and we go to the field and see what's actually there to label the objects. We put all this in a computer, which produces a model able to predict the label of unkown objects.

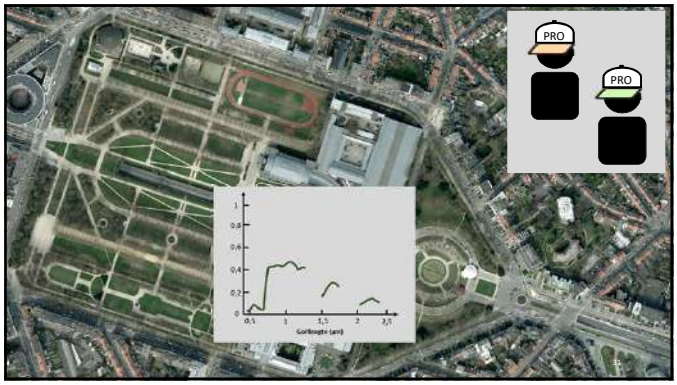
If we apply this on a map, we get this nice classification output.



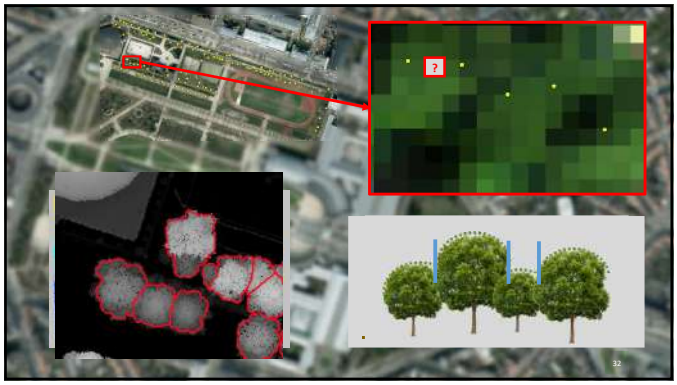
Looking at more detail, there are still some errors in the output, particularly in shadowed areas or near object boundaries. We specifically focused our efforts on improving the outcomes in those problem areas and in the end found a result that reasonably matches reality. Some green types however remain very difficult to distinguish (for instance flower beds and low shrubs), and some are very easy to distinguish (for instance green roofs, because they are spectrally quite dissimilar from other types).



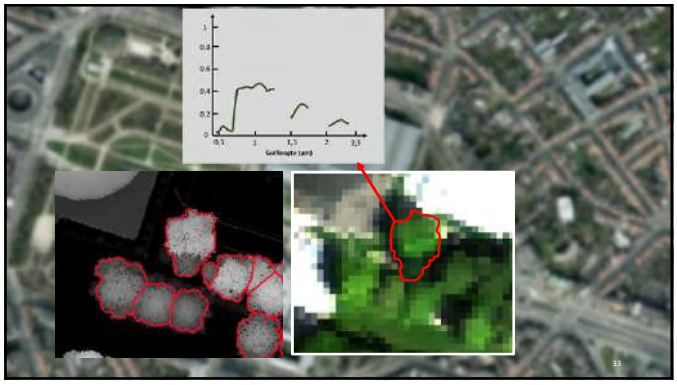
Last part of the phd was about retrieving properties of urban green.



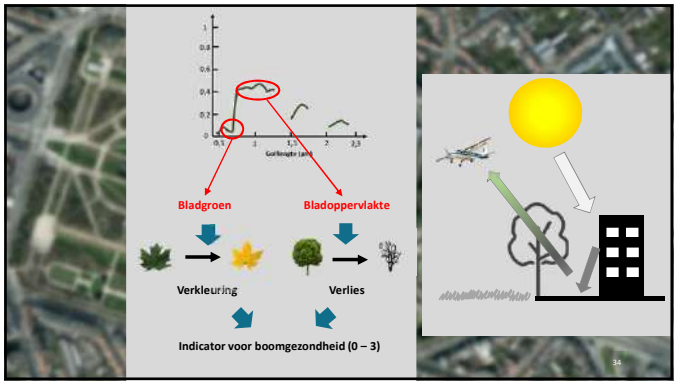
We were contacted by a consultancy firm with the question of assessing the health of the trees in Jubelpark, Brussels, because they had done two ground surveys of the park which resulted in totally contrasting findings. As the spectral curve of the tree depends on its properties, this would be an easy job for us...



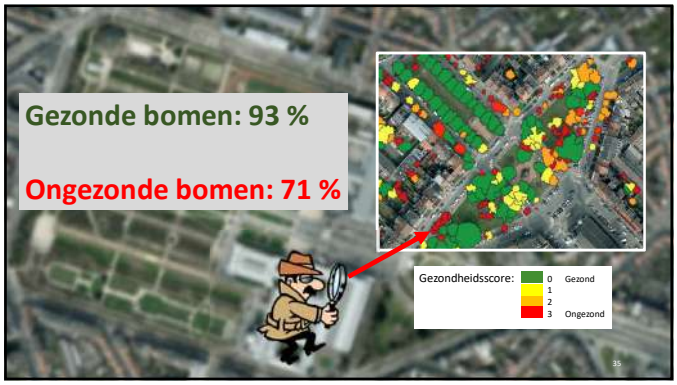
We got some locations of trees and whether they were healthy or not... Problem: due to the low resolution of our data, we can't clearly see which pixel belongs to which tree... We again turned to lidar data to delineate the individual trees using a two-stage approach in which we first separated trees from the rest and then seperated the individual trees.



Once delineated, we extracted the mean spectral signal of each tree.



A lot of methods now exist to extract properties from this signal. However, they were all designed in homogeneous forest areas and not equipped to cope with disturbing background effects you find in cities. Main challenge here was to eliminate those background effects. Once that was done, we extracted chlorophyll content and leaf area index and combined this information to an objective tree health indicator on a 0-3 scale.



Comparing our approach with field assessments revealed that we were able to detect healthy trees with an accuracy of 93% and unhealthy trees with 71%.

In the end we got such a map, which can provide a first indication on problems regarding tree health in the city.

To sum up:

First part was about unmixing cocktails. We created an algorithm to find the most relevant ingredients and used lidar data as supplementary information during the unmixing itself.

Second part was about distinguishing very similar urban green types, where we moved from pixels to objects and fancy computer models and found that some were easy to distinguish and others not.

Finally, we produced a tree health map by delineating each individual tree, tackling background effects and extracting relevant properties for each tree.

What do you need to remember?

If you can't see what's in a cocktail based on the color, TASTE it!

Meaning that: given the sheer diversity of remote sensing technology, it is our job is to combine these in smart ways to extract the information we need.

Urban green is a valuable tool to create enjoyable, sustainable and resilient cities!

Everyone can contribute to this bright future by making sure his/her garden consists of a health mixture of different plant types, each providing different services. Your neighbours will be grateful for your efforts! ;)

Thank you!