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National Aerospace Laboratory NLR

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Contents

2 Figures

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ABSTRACT

In a modelling case study it has been investigated whether it would be possible to retrieve from optical remote sensing data the (bio)physical parameters of the coupled soil-vegetation-atmosphere system that have an effect on spectral radiances detected by spaceborne sensors. For this, optical data on single leaves generated by means of the PROSPECT model have been applied in the integrated optical soil-canopy-atmosphere radiation model OSCAR. The influences of two soil parameters, two leaf parameters, four canopy parameters and three atmospheric parameters on hyperspectral directional planetary reflectances have been simulated in a model inversion experiment.
The simultaneous retrieval of the 11 parameters has been tested using classical model inversion by means of the Gauss-Newton method of non-linear least squares parameter estimation. Preliminary results indicate that this approach has some potential, as in a number of widely differing cases the retrieval of all model parameters from 10 nm resolution hyperspectral red edge planetary reflectance data under five directions was successful.

Keywords: bidirectional reflectance, vegetation canopies, SAIL, PROSPECT, model inversion, Gauss-Newton, parameter retrieval, biophysical parameters, atmosphere, hyperspectral data

1. INTRODUCTION

The estimation of biophysical parameters of vegetation canopies from optical remote sensing data is very important for the study of land surface processes. Traditionally, this has been realised mostly by means of spectral indices, e.g. the normalised difference vegetation index (NDVI), which is derived from spectral reflectances or radiances in the near infrared and red parts of the spectrum. Spectral indices have the advantage that they can be applied very easily and that they sometimes have a fairly high correlation with a surface parameter such as fractional vegetation cover. However, the spectral reflectance of vegetation canopies is influenced by many factors simultaneously, so it is not very likely that one can obtain a good relationship between a spectral index and a single variable when other parameters vary at the same time.
In the previous SASSSIS study [1] it was shown by means of model simulations that canopy LAI might be retrieved from multiple linear regression equations based on TOA multispectral (i.e. seven bands) radiance observations under five different viewing directions at an accuracy of about 12%. In this study, most variations found in reality were included, such as variation of soil type, leaf type, canopy structure, solar zenith angle and atmospheric conditions. However, it is known that the relations between surface parameters and spectral radiances are non-linear, so better retrieval results should be possible when taking these non-linear relationships into account.
The reason that the red and the near infrared are used so often to map green vegetation is that the absorption of radiation in a green leaf canopy is so different in both wavelength regions. In the red there is a strong absorption due to chlorophyll in the leaves, whereas in the near infrared there is almost no absorption at all. When the leaves are green, this great difference in absorption leads to a strong spectral response due to variation of LAI over a spectrally nearly flat soil background. This behaviour is the basis under any red – near infrared vegetation index. However, what would happen if the leaves turned yellow due to chlorophyll demolition? In that case there would be a strong spectral response as well, but it might easily be mistaken for a large decrease in canopy LAI.

From radiative transfer theory it is known that the relation between a quantity called infinite reflectance and the single scattering albedo of the medium is highly non-linear. The single scattering albedo is one minus the fraction of the intercepted radiation that is absorbed, so the absorption coefficient of the material also has a non-linear influence on the reflectance. This also holds when the optical thickness of the medium is less than infinite. For weak absorption we see an almost linear relationship between optical thickness and reflectance, whereas for strong absorption this relationship is strongly (negative) exponential. Altogether, this means that in a region where the absorption coefficient varies significantly with wavelength, the shape of the spectral reflectance curve will change with the optical thickness. In other words, when the reflectance at two wavelengths is given, the reflectance at a wavelength halfway between the first two will contain additional information, because the shape of the spectrum changes with optical thickness, even if the absorption coefficient varies linearly in the interval. This is a strong motivation to the need for high spectral resolution in certain wavelength regions. For leaf canopies the above effects come to expression as follows:

- When the leaf chlorophyll concentration decreases, this is first noticed at the wavelengths where chlorophyll absorption is weakest, i.e. in the red edge close to the near infrared and in the green. Only when it decreases much further, an effect in the red becomes visible. In the actual near infrared nothing will change in the canopy reflectance, however, as there is no sensitivity to leaf chlorophyll in that part of the spectrum.
- When the canopy LAI decreases from a high value at high leaf chlorophyll concentration, it is first noticed in the near infrared, because leaf absorption is minimum there. When LAI is low, sensitivity to LAI changes is greatest in the red.

This is also demonstrated in Fig.1, which shows the modelled canopy reflectance times 10000 in the red edge for a series of combinations of LAI and leaf chlorophyll concentration. The LAI varies according to the series 0, 0.25, 0.5, 1, 2, 4 and 8. Chlorophyll concentration is given by the series 15, 20, 25,…, 60, 70 and 80 μg / cm^2. The spectral bands represent the wavelength range from 670 to 800 nm at 10 nm intervals.

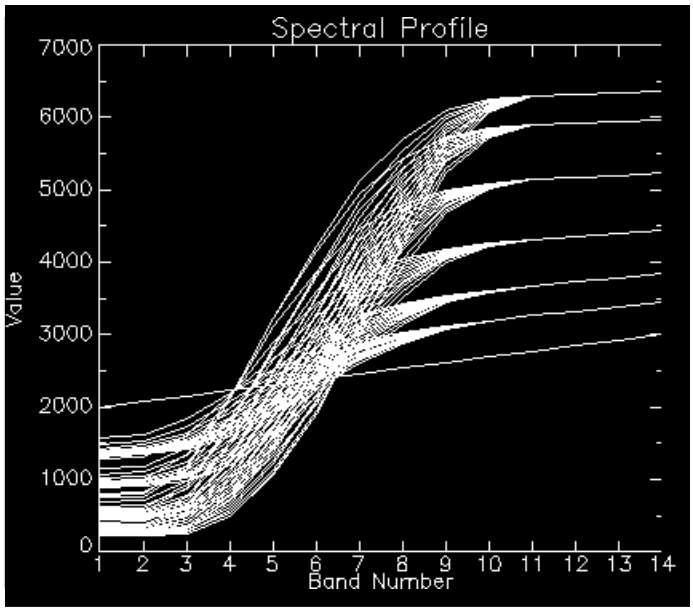

Fig.1 Effects of leaf chlorophyll and LAI on canopy reflectance in the red edge

The position of the red edge point clearly moves to longer wavelengths for higher chlorophyll contents, but the canopy LAI complicates this simple relationship, and incorporation of other parameters would complicate it even more. It can be concluded that leaf chlorophyll concentration and canopy LAI act in

different ways on spectra of the vegetation canopy reflectance in the red edge region. Due to this, it should also be possible to retrieve both parameters from high resolution spectral reflectance data in this region. Note, that with spectral reflectance data from red and near infrared alone this is not possible: several combinations of leaf chlorophyll concentration and canopy LAI can give the same combination of red and near infrared reflectance, so it would be impossible to retrieve both parameters from spectral data in the red and near infrared alone. However, hyperspectral data from the red edge region not only tell us the reflectance at both ends, but also the shape of the curve in between, and this enables us to retrieve both parameters. There have been numerous studies on the use of the red edge point (the wavelength where the first spectral derivative is maximum) as an indicator for LAI and other vegetation parameters and on how the red edge point can be derived best from hyperspectral data [2, 3, 4, 5, 6]. However, the red edge position has the same disadvantage as the NDVI, namely that it responds to several parameters simultaneously, so that no single one can be retrieved accurately, unless all other ones are constant, which of course is not very likely.
The red edge spectral region (670 – 800 nm) is very suitable for information on leaf chlorophyll, as in this region the chlorophyll absorption coefficient varies from very high to zero, so a large dynamic range is traversed in a relatively short wavelength interval. Also, few other optical parameters vary in this range, and the ones that do, vary only little. Therefore this region was chosen as the spectral interval of the model inversion experiment.
While leaf chlorophyll concentration and canopy LAI may be the most interesting biophysical parameters to be retrieved from remote sensing data, in reality other canopy parameters, leaf parameters, soil parameters, and atmospheric properties are expected to vary as well and are having an influence on spectral reflectances, so for some degree of realism these should also be considered in the numerical experiment.

2. METHODS

Model inversion experiments with several canopy reflectance models have already been carried out since the work of Goel and Thompson [10, 11] in 1984. In most of these experiments the model is called iteratively and a merit function is defined which indicates the squared distance to the solution and in which sometimes a penalty function is incorporated to avoid the exceeding of parameter boundaries. The iteration stops when the model outputs match with measured spectral data (Fig.2).

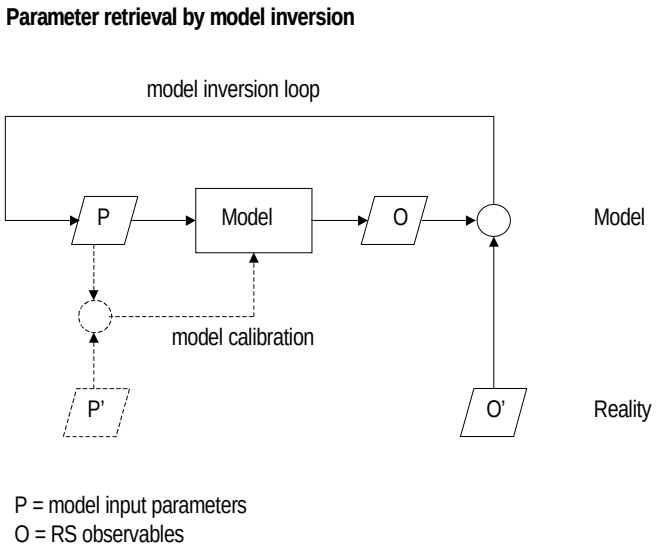

Fig.2 Model inversion loop and model calibration based on measured parameters

Models can be calibrated (dashed lines) if measured observables and parameters are both available. In the case of many output parameters, such as with hyperspectral and multidirectional data, the single quadratic merit function is formed out of information from a large number of "channels". In this approach, the model inversion algorithm has to get its information on how to change the parameters in the direction of a solution from the Hessian, the matrix of second order partial derivatives of the merit function with respect to the parameters. As in this method all squared deviations from the target pattern are added up to form the merit function, information on how to improve the fit in a subspace of the patterns is lost. Therefore, in this section an alternative is proposed, the well-known Gauss-Newton method. Here the information on how to change the parameters in the right direction is derived from the Jacobian, which is the matrix of first partial derivatives of all model output variables with respect to the input parameters. It will be clear that in this case much more information on how to change the parameters is directly available. Therefore, this method is preferred. This method proceeds as follows:

Let the Jacobian matrix $\mathbf{J}$ be defined by

$$\Delta \mathbf{r} = \mathbf{J}\,\Delta \mathbf{p}\,,$$

where $\Delta \mathbf{p}$ is a small change in the parameter vector, and $\Delta \mathbf{r}$ the change in the vector of spectral-directional reflectances, then multiplication by the transposed of $\mathbf{J}$ gives

$$\mathbf{J}^{\mathbf{T}}\Delta \mathbf{r} = \mathbf{J}^{\mathbf{T}}\mathbf{J}\,\Delta \mathbf{p}\,, \quad \text{or}$$

$$\Delta \mathbf{p} = (\mathbf{J}^{\mathbf{T}}\mathbf{J})^{-1}\mathbf{J}^{\mathbf{T}}\Delta \mathbf{r}\,.$$

The numerical stability of the Gauss-Newton method can greatly be improved by means of the Levenberg-Marquardt algorithm, which is based on the modified equation

$$\Delta \mathbf{p} = (\mathbf{J}^{\mathbf{T}}\mathbf{J} + \mu \mathbf{I})^{-1}\mathbf{J}^{\mathbf{T}}\Delta \mathbf{r}\,,$$

where μ is a scalar parameter that is used to control the numerical behaviour of the algorithm. When this parameter is high, the conversion to the solution follows the steepest descent direction and therefore is secure but slow. When it is low, the Gauss-Newton direction is approximately followed, which is fast in the neighbourhood of the final solution, but unstable and possibly slow otherwise. Therefore one usually starts with a high value of the parameter, and when good progress is made, as evidenced by a decreased distance to the solution, the parameter is lowered by a certain factor. If the distance to the solution turns out to have increased, this may lead to instability, and in that case the parameter is increased in order to regain control via the steepest descent direction.

Regarding the model simulations, the following procedure was followed:

Spectra of the single leaf reflectance and transmittance in the red edge region have been simulated for a range of chlorophyll concentrations C_{ab} and 3 values of the leaf mesophyll parameter N by means of the PROSPECT model [7]. The simulations have been carried out for the wavelength range 670 – 800 nm with 10 nm steps, thus resulting in optical data at 14 wavelengths. Chlorophyll concentrations used were 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 70 and 80 $\mu g/cm^2$ (12 values) and the 3 values of the mesophyll parameter were 1.0, 1.5, and 2.0.
In a first numerical experiment, the data generated by PROSPECT were used in combination with a very simple Kubelka-Munk type canopy reflectance model in order to verify whether canopy LAI and leaf chlorophyll indeed gave different spectral responses in the red edge region. In this experiment also the soil brightness and the soil's spectral slope were varied. This enabled us to evaluate methods of compensating for soil background effects by means of first and second spectral derivatives.

In the next step the simple KM-type model was replaced by the SAILH model and a model inversion experiment was carried out in order to verify whether the most important parameters could be retrieved from hyperspectral bidirectional reflectance data. The SAILH model [9] is an extended version of the SAIL model [8] to include the hot spot effect. Here the parameters to be retrieved in the groups soil, canopy and leaf were:

Soil brightness
Soil spectral slope

Canopy LAI
Average leaf slope
Bimodality parameter of the LIDF
Canopy hot spot parameter

Leaf chlorophyll concentration
Leaf mesophyll parameter

In this experiment the solar zenith angle, the viewing zenith angle and the relative azimuth were all held fixed and no diffuse incident light on the canopy top was assumed. During the development of the model inversion procedure several enhancements were introduced, such as transformations to the input parameters in order to avoid problems due to strong non-linearity and due to the interactions between parameters and their valid ranges.
In the last experiment the SAILH model was replaced by the OSCAR model in order to further enhance the degree of realism.
The model OSCAR (Optical Soil-Canopy-Atmosphere Radiance) [9] is an integrated model in which SAILH has been interfaced with the soil's reflectance and scattering in the atmosphere. The number of parameters was increased from 8 to 11 by incorporation of 3 atmospheric parameters, namely:

Visibility at sea level in km
Aerosol Ångström coefficient
Aerosol single sacttering albedo

Also, in order to simulate TOA observations, the planetary reflectance was used as the remote sensing observable on which model inversion was based. As in the previous experiment it already became clear that retrieval of the LIDF parameters was the most difficult if only one direction was applied, it was decided to include more directions. For this, the five best directions for estimation of LAI from planetary reflectance data, as resulting from the SASSSIS [1] study, were chosen. These are:

Viewing zenith	Azimuth
38	120
69	120
52	90
38	0
69	180

Multiplied by the number of spectral bands this gives 70 hyperspectral-directional data points on which a model inversion can be based.
The OSCAR model allows also variation of the target surroundings for modelling of the adjacency effect [9], but in this experiment the optical properties of the surroundings were held constant in order to avoid too much complications.

The model input parameters and possibly their transformations are described below:

It is assumed that the soil reflectance changes linearly with wavelength in this short interval. The soil's reflectance in the interval is described by means of the parameters P_1 and P_2, called brightness and spectral slope. They are defined by

$P_1 = (R_{670} + R_{800}) / 2$, and
$P_2 = R_{800} / R_{670}$,

where R_{670} and R_{800} are the soil's reflectance at 670 and 800 nm, respectively. From these parameters the soil's reflectance at any wavelength can always be reconstructed.
The ranges for the parameters considered during model inversion were 0 – 0.6 for P_1 and 1.0 – 1.5 for P_2.

LAI is transformed to $P_3 = \exp(-0.2\ LAI)$. This reduces non-linearity, especially in the near infrared, and the valid range becomes 0 – 1.
The LIDF parameters *a* and *b* of the SAILH model are related to average leaf slope and bimodality of the leaf inclination distribution function, respectively [9]. Both parameters can vary from –1 to 1, but not independently, as the sum of their absolute values should stay less than or equal to unity. Therefore, these parameters are transformed into:

$P_4 = 0.5\ (a + b + 1)$
$P_5 = 0.5\ (a - b + 1)$

These parameters both range (independently) from 0 to 1 when *a* and *b* are in the valid range.

Parameter P_6 is the hot spot parameter and it is supposed to vary between 0 and 0.5.

Parameters P_7 and P_8 are the leaf parameters, describing chlorophyll concentration and the leaf mesophyll parameter. During model inversion, care must be taken to ensure that the leaf parameters actually are integer numbers in this case, as the PROSPECT model had not been integrated into OSCAR, but rather use was made of simulation results obtained with PROSPECT for discrete cases of these parameters in an earlier stage. Therefore, P_7 is an integer from 1 to 12, and P_8 is an integer from 1 to 3. In the model inversion results discussed later, these parameters are presented as real numbers, because there the predictions of the correct parameters are shown, not the values actually used in the simulations.

The atmospheric parameter visibility *V* has a strongly non-linear effect on the optical properties of the atmosphere. A change from 6 to 5 km may have more effect than a change from 50 to 30 km visibility. Therefore, this parameter is replaced by

$P_9 = \exp(-0.1\ V)$.

This reduces non-linearity for the atmospheric effects and the valid range becomes 0 – 1.

The other atmospheric parameters are P_{10}, the aerosol Ångström coefficient, which is assumed to vary from –0.6 to –1.3, and P_{11}, the aerosol single scattering albedo. This parameter is assumed to vary from 0.6 to 1.0.

3. RESULTS

In this section some examples of results of model inversion are discussed. In the first example below the 11 target parameters and the associate planetary reflectances times 10000 at the 14 wavelengths and in the 5 viewing directions are shown first. In the current implementation the starting guess is always at the

centre of parameter space. This choice is shown, followed by the associate reflectance values. After this are shown in one line: the iteration count, the current sum of the squared errors, and the Levenberg-Marquardt parameter of the Gauss-Newton algorithm and this pattern is repeated for all iterations. When this result was obtained, the visibility parameter was still untransformed, so for instance the target visibility is really 15 km here.

Results of model inversion program output

```
0.20  1.10  0.70  0.25  0.40  0.10 10.00  2.00 15.00 -0.90  0.85      target parameters

583  576  626  896 1401 2019 2726 3268 3657 3816 3880 3900 3919 3939  modelled spectral data
771  760  806 1060 1529 2101 2749 3242 3597 3745 3809 3833 3857 3881  14 wavelengths, 5 directions
645  636  685  953 1453 2064 2760 3292 3675 3831 3896 3916 3937 3958
775  763  818 1124 1693 2374 3138 3716 4128 4295 4363 4385 4407 4428
827  815  860 1112 1576 2142 2785 3276 3629 3775 3838 3861 3884 3907

0.31  1.25  0.50  0.50  0.50  0.25  6.50  2.00 21.25 -0.95  0.80      starting guess

514  506  589  942 1544 2266 3114 3799 4320 4542 4637 4670 4702 4735  associate spectral data
686  674  745 1061 1603 2250 2994 3583 4025 4217 4302 4336 4369 4403
574  565  645  997 1597 2313 3147 3817 4323 4540 4633 4667 4700 4733
737  727  831 1273 1998 2827 3763 4501 5054 5291 5393 5431 5468 5506
729  716  788 1104 1644 2287 3029 3616 4057 4248 4333 4366 4399 4432

 1   0.185665    1.00000E-05                                          iteration count, distance,
                                                                      L-M parameter
0.38  1.37  0.70  0.27  0.50  0.02  6.93  1.41 21.04 -0.70  0.86

624  621  686  993 1554 2231 2981 3546 3951 4131 4222 4269 4318 4366
774  764  829 1132 1667 2302 3001 3523 3895 4059 4138 4179 4220 4261
674  668  732 1038 1596 2266 3008 3564 3962 4138 4225 4271 4317 4363
779  771  835 1157 1752 2460 3238 3818 4233 4415 4506 4553 4601 4650
826  816  883 1189 1724 2356 3052 3572 3943 4106 4185 4225 4266 4307

 2    4.01375E-02    1.00000E-06

0.29  1.30  0.69  0.15  0.53  0.07  8.33  1.84 20.76 -0.70  0.84

588  583  654  978 1543 2212 2952 3508 3904 4070 4145 4176 4207 4239
750  740  802 1098 1619 2236 2919 3430 3794 3948 4018 4049 4079 4110
645  638  707 1027 1586 2246 2976 3523 3911 4075 4148 4180 4211 4242
779  770  851 1224 1862 2596 3392 3981 4397 4571 4649 4683 4716 4750
798  787  848 1138 1651 2259 2935 3441 3802 3954 4024 4053 4083 4113

 3    2.56181E-02    1.00000E-07

0.20  1.32  0.71  0.23  0.42  0.09 10.42  2.06 20.03 -0.70  0.87

575  569  622  898 1412 2040 2754 3300 3692 3854 3923 3948 3973 3998
759  748  797 1061 1549 2141 2811 3320 3685 3837 3904 3929 3955 3981
636  628  680  956 1468 2092 2799 3338 3726 3886 3954 3979 4004 4029
764  754  812 1128 1709 2403 3176 3758 4173 4344 4418 4444 4471 4498
810  798  846 1108 1590 2176 2839 3344 3707 3858 3924 3949 3974 3999

 4    1.84876E-03    1.00000E-08

0.19  1.23  0.72  0.25  0.36  0.10 11.10  2.24 17.98 -0.70  0.86

575  568  608  847 1322 1925 2638 3201 3616 3787 3858 3879 3901 3922
762  750  790 1026 1479 2046 2704 3217 3593 3750 3817 3841 3865 3888
636  628  667  907 1380 1979 2682 3236 3642 3810 3880 3902 3924 3946
765  754  796 1066 1601 2268 3041 3644 4083 4264 4338 4362 4385 4409
815  803  842 1076 1526 2087 2740 3250 3623 3779 3846 3869 3892 3915

 5    1.26706E-03    1.00000E-09

0.19  1.11  0.71  0.26  0.37  0.10 10.23  2.29 15.03 -0.90  0.85

585  578  629  899 1404 2021 2722 3257 3640 3796 3860 3879 3899 3918
774  762  808 1062 1531 2101 2745 3234 3585 3730 3794 3817 3841 3864
647  638  687  956 1455 2064 2755 3281 3658 3811 3875 3895 3916 3937
776  764  819 1126 1693 2371 3128 3698 4103 4267 4335 4356 4378 4400
830  817  863 1115 1579 2144 2783 3269 3618 3762 3824 3847 3870 3893

 6    1.35831E-04    1.00000E-10
```

```
0.20  1.10  0.70  0.25  0.40  0.10 10.23  2.29 15.00 -0.90  0.85

584  576  627  896 1401 2019 2726 3268 3658 3816 3880 3900 3919 3939
772  760  806 1060 1529 2101 2749 3243 3598 3745 3810 3833 3857 3881
646  636  685  953 1453 2064 2760 3292 3675 3831 3896 3917 3937 3958
775  763  818 1124 1693 2374 3138 3716 4128 4295 4363 4385 4407 4428
827  815  861 1112 1577 2143 2785 3276 3629 3775 3838 3861 3884 3907

 7    1.03011E-07    1.00000E-11

0.20  1.10  0.70  0.25  0.40  0.10 10.23  2.29 15.00 -0.90  0.85

584  576  627  897 1401 2020 2726 3268 3658 3816 3881 3900 3920 3939
772  760  806 1060 1530 2101 2749 3243 3598 3746 3810 3834 3857 3881
646  636  686  954 1453 2064 2760 3293 3675 3831 3896 3917 3938 3958
775  763  818 1125 1693 2375 3139 3716 4128 4295 4364 4385 4407 4429
828  815  861 1112 1577 2143 2786 3276 3629 3775 3839 3862 3885 3908

 8    6.04075E-11    1.00000E-12
```

From the above example it becomes clear that already in 8 iterations an accurate solution is obtained in this case. In other cases more iterations may be required to reach a solution, but it has been demonstrated that in principle it is possible to retrieve all parameters in this way, useful biophysical parameters as well as ones that can be considered disturbing factors.

4. CONCLUSIONS

It has been demonstrated that, at least theoretically, it is possible to retrieve important (bio)physical parameters from red edge hyperspectral remote sensing data acquired under different directions. The most important of these parameters are soil brightness in the red edge region, leaf chlorophyll concentration, canopy leaf area index and atmospheric visibility. This can be very relevant for the study of land surface processes.

Simultaneous retrieval of all radiometrically relevant parameters is aimed at the estimation of biophysically interesting parameters such as leaf chlorophyll and canopy LAI, while at the same time the factors influencing the relationships between these parameters and remotely sensed data are also estimated. If the retrieval of all parameters is correct, it means that also the disturbing influences are known, so that the accuracy of the retrieved parameters of interest will be higher than when these factors are ignored.

Classical model inversion of hyperspectral multidirectional planetary reflectance data requires enormous processing efforts, so for application in practice it is recommended to investigate accellerations in numerical modelling, possibilities for improving convergence, and alternatives such as artificial neural networks.

The results obtained are still very preliminary. A more comprehensive investigation should also consider the influence of instrumental noise and a more realistic modelling of the adjacency effects and of gaseous absorption in the atmosphere. From an operational point of view it would be important to investigate how a less dense spectral and directional sampling would influence the success of parameter retrieval.

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6. REFERENCES

1. W. Verhoef and M. Menenti, “Spatial and Spectral Scales of Spaceborne Imaging Spectro-radiometers”, Final Report NLR-CR-98213 under ESA/ESTEC contract no. 12072/96/NL/CN, National Aerospace Laboratory NLR, Amsterdam, The Netherlands, 1998.
2. E.W. Hare, G.R Miller and G.R Edwards, “Studies of the Vegetation Red Reflectance Edge in Geobotanical Remote Sensing”, Proc. 9th Can. Symp. Rem. Sens., St. Jones, New Foundland, pp. 433-440, 1984.

3. C.E. Leprieur, “Preliminary evaluations of AVIRIS airborne measurements for vegetation”, 9th EARSeL Symposium, Espoo, Finland, pp.524-530, 1989.
4. G. Guyot and F. Baret, “Utilisation de la haute résolution spectrale pour suivre l’état des couverts végétaux”, Proc. 4th Int. Coll. on Spectral Signatures of Objects in Rem. Sens., Aussois, France, ESA SP-287, pp. 279-286, 1988.
5. H. Bach, “Die Bestimmung hydrologischer und landwirtschaftlicher Oberflächenparameter aus hyperspektralen Fernerkundungsdaten”, PhD Thesis, University of Munich, 1995.
6. H. Bach and W. Mauser, “Improvements of plant parameter estimations with hyperspectral data compared to multispectral data”, *Remote Sensing of Vegetation and Sea*, SPIE Vol. 2959, pp. 59-67, 1997.
7. S. Jacquemoud and F. Baret, “PROSPECT: a model of leaf optical properties spectra”, Rem. Sens. of Env. 34: 75-91, 1990.
8. W. Verhoef, “Light scattering by leaf layers with application to canopy reflectance modeling: the SAIL model”, Rem. Sens. of Env. 16:125-141, 1984.
9. W. Verhoef, “Theory of radiative transfer models applied in optical remote sensing of vegetation canopies”, PhD Thesis, Wageningen Agricultural University, 1998.
10. N.S. Goel and R.L. Thompson, “Inversion of vegetation canopy reflectance models. IV. Total inversion of the SAIL model”, Rem. Sens. of Env. 15: 237-253, 1984.
11. N.S. Goel, “Models of vegetation canopy reflectance and their use in estimation of biophysical parameters from reflectance data”, Rem. Sens. Reviews 4:1-212, 1988.