Generation of Spectral–Temporal Response Surfaces by Combining Multispectral Satellite and Hyperspectral UAV Imagery for Precision Agriculture Applications

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Abstract—Precision agriculture requires detailed crop status information at high spatial and temporal resolutions. Remote sensing can provide such information, but single sensor observations are often incapable of meeting all data requirements. Spectral–temporal response surfaces (STRSs) provide continuous reflectance spectra at high temporal intervals. This is the first study to combine multispectral satellite imagery (from Formosat-2) with hyperspectral imagery acquired with an unmanned aerial vehicle (UAV) to construct STRS. This study presents a novel STRS methodology which uses Bayesian theory to impute missing spectral information in the multispectral imagery and introduces observation uncertainties into the interpolations. This new method is compared to two earlier published methods for constructing STRS: a direct interpolation of the original data and a direct interpolation along the temporal dimension after imputation along the spectral dimension. The STRS derived through all three methods are compared to field measured reflectance spectra, leaf area index (LAI), and canopy chlorophyll of potato plants. The results indicate that the proposed Bayesian approach has the highest correlation \((r = 0.953)\) and lowest RMSE \((0.032)\) to field spectral reflectance measurements. Although the optimized soil-adjusted vegetation index (OSAVI) obtained from all methods have similar correlations to field data, the modified chlorophyll absorption in reflectance index (MCARI) obtained from the Bayesian STRS outperform the other two methods. A correlation of 0.83 with LAI and 0.77 with canopy chlorophyll measurements are obtained, compared to correlations of 0.27 and 0.09, respectively, for the directly interpolated STRS.

Index Terms—Crop phenology, data fusion, hyperspectral imaging, image resolution, precision agriculture.

I. INTRODUCTION

In the context of threatened global food security, precision agriculture is one strategy which can maximize yield to meet increased food demands, while minimizing the economic and environmental costs of food production [1]. Precision agriculture requires detailed information regarding temporal and spatial variations in crop conditions, which can be obtained through remote sensing [1]. The specific data requirements depend on the intended application. For example, the required spatial resolution could be 5–10 m for variable rate application of fertilizer, 1–3 m for crop biomass and yield prediction, and 0.5–1 m for weed control applications [2]. The required spectral resolution also depends on the application. Hyperspectral indices are capable of targeting reflectance at specific wavelengths for estimating chlorophyll [3], canopy nitrogen content [4], and carotenoids [5]. Narrowband vegetation indices obtained from hyperspectral data have been shown to obtain higher correlations to crop leaf area index (LAI) [6] and chlorophyll content [7] than broadband indices.

The use of satellite imagery to support agricultural applications has been recognized since the 1970s [2]. However, inadequate spatial and spectral resolutions as well as insufficient revisiting frequencies have largely impaired the use of satellite sensors for crop management [8]. Recently, some studies have shown that hyperspectral systems can be mounted on unmanned aerial vehicles (UAVs) [9]. The hyperspectral mapping system (HYMSY) developed at Wageningen University under the Smart Inspectors project [10] is one such example. Flexible image acquisition dates and user-controlled spatial resolution as well as flight paths are the benefits of such a system.

However, UAV image acquisition is also paired with high operational costs [9] which may therefore limit the number of high-resolution UAV images available. This is problematic, as the temporal dynamics of crop surface reflectance are important for crop monitoring and yield prediction applications [11], [12]. One solution is to supplement hyperspectral data with satellite observations at lower spectral resolutions. This could provide a more complete representation of the temporal dynamics of spectral reflectance, especially during growing seasons or comparing relatively new hyperspectral data with historical satellite data to improve decision-making in precision agriculture [2].

Fusing images from two different sensors may provide datasets which exceed physical limitations of each individual
sensor. For example, Roy et al. [13] presented the spatial
temporal adaptive reflectance fusion model (STARFM),
to fuse Landsat and MODIS imagery which allows the user
to obtain synthetic imagery with a spatial resolution of 30 m at
daily interval. However, this method requires the two
types of imagery at different spatial resolution to have correspond-
ing spectral bands, and can be sensitive to temporal changes
[14], [15] use unmixing-based techniques for spatial–temporal
fusion, which eliminates the corresponding-band requirements
in the STARFM method and allows for the downscaling of
additional spectral bands from medium spatial resolution sen-
sors. Similarly, Fasbender et al. [16] present a pan-sharpening
approach with a Bayesian framework which compared favor-
able to other pan-sharpening methods. However, in the current
application, the high-resolution imagery (hyperspectral UAV)
have a higher spectral resolution than the medium-resolution
imagery (multispectral Formosat-2). The motivation of the cur-
current study is to investigate methods which can retain valuable
hyperspectral information from the UAV imagery and use addi-
tional information from multispectral observations to obtain a
more complete temporal profile.

Two previous studies [17], [18] combined multiple sources of
imagery to create a reflectance spectrum, continuous along both
temporal and spectral domains. This creates a four-dimensional
(4-D) dataset (latitude, longitude, wavelength, date) known in
literature as a spectral–temporal response surface (STRS) [17]
or spectral–temporal analysis by response surface [18].
The surfaces were formed by interpolating the reflectance of each
pixel along the spectral and temporal dimensions. Mello et al.
[18] utilized the polynomial trend surface (PTS) and collo-
cation surface (CS) methods to combine Landsat-7/ETM+
and Landsat-5/TM imagery to differentiate between sugarcane
harvest methods in Brazil. Villa et al. [17] focused on the devel-
opment of an STRS methodological framework. Their study
utilized a two-step interpolation technique: first interpolating
MERIS and MODIS spectra along the wavelength dimension
using a spline interpolation, and then interpolating along the
temporal dimension.

However, these two approaches have a number of limita-
tions. First, they do not account for the physical characteristics
of reflectance spectra. Therefore, the interpolated spectra may
be unrealistic, such as a missing red-edge for vegetation spec-
tra. Second, all reflectance observations are weighted equally
and the uncertainties of each measurement are not taken into
account. Third, these studies combine two sensors with similar
spectral characteristics. However, the current study combines
multispectral satellite imagery with only four spectral bands
with hyperspectral imagery (101 bands) from an UAV. The
differences between the spectral characteristics of both sensors make it more difficult to directly compare reflectance
measurements.

To overcome these difficulties, the current study proposes a
new methodology to obtain STRS based on Bayesian theory,
which allows the uncertainties to be quantified [19]. First, the
multispectral reflectance spectra are imputed to the hyperspec-
tral intervals based on the a priori covariance between spectral
bands of similar signatures. This causes the interpolated spec-
tra to retain the physical features characteristic of vegetation
spectra, even when combining multispectral and hyperspectral
images. Second, the temporal interpolation utilizes Bayesian
inference and takes observation uncertainties into account.

The objective of this study is to present a new method to
combine hyperspectral and multispectral imagery into STRS.
This Bayesian method is compared to two other STRS meth-
ods based on [17] and [18]. All three methods are tested for a
potato field in The Netherlands during the 2013 growing sea-
son. Extensive field measurements of crop reflectances, LAI,
and canopy chlorophyll are utilized to evaluate the quality of
the STRS results for the three methods.

II. THEORY

A. Spectral Interpolation: Bayesian Imputation

Hyperspectral observations of vegetation often present high
correlations between spectral bands [20]. The current paper
assumes that given the a priori covariance of hyperspectral
bands, a hyperspectral reflectance spectrum can be inferred
from the multispectral imagery using Bayesian imputation.

Suppose $x_{m,i}$ represents the surface reflectance factor at the
wavelengths of the multispectral sensor and $x_{h,i}$ represents the
unknown hyperspectral surface reflectance factors at date $i$.
These distributions are jointly Gaussian defined by (1) with the
marginal (2) and (3)

$$
\mu = \left( \frac{\mu_h}{\mu_m} \right), \sum = \left( \begin{array}{cc}
\Sigma_{hh} & \Sigma_{hm} \\
\Sigma_{mm} & \Sigma_{mm}
\end{array} \right) \tag{1}
$$

$$
p(x_h) = N(x_h | \mu_h, \sum_{hh}) \tag{2}
$$

$$
p(x_m) = N(x_m | \mu_m, \sum_{mm}) \tag{3}
$$

Given the a priori mean ($\mu_m$) and distribution ($\Sigma_{mm}$) of
the multispectral reflectance factors and the covariance matrix
$\sum_{hh}$ of the hyperspectral reflectance data, the posterior condi-
tional distribution (4) can be obtained by computing the model
parameters described in (5) and (6) [19]

$$
p(x_h | x_{m,i}) = N(x_h | \mu_{h,m}, \sum_{h|m}) \tag{4}
$$

$$
\mu(x_h | x_{m,i}) = \mu_h + \sum_{h} h \sum_{mm}^{-1} (x_m - \mu_m) \tag{5}
$$

$$
\sum_{h} (x_h | x_{m,i}) = \sum_{hh} - \sum_{hm} \sum_{mm}^{-1} \sum_{mh} \tag{6}
$$

The estimation $\hat{x}_{ij}$ of the missing spectral value is defined as
the mean value of the posterior predictive presented in (4). It
can be calculated as follows:

$$
\hat{x}_{ij} = E[x_j | x_{m,i}, \theta] \tag{7}
$$

where $\theta$ refers to the model parameters, and $x_j$ refers to the
reflectance at wavelength $i$.

Although hyperspectral bands display a high covariance
between wavelengths, the nature of this covariance will vary
depending on the surface properties, i.e., fractions of bare
ground or vegetation. This implies that the covariance between
hyperspectral and multispectral wavelengths will vary according to different land cover types and must be calculated, accordingly. The current implementation selects a large number \((n = 100)\) of hyperspectral signatures which are very similar to the multispectral signatures which are to be imputed. These observations are used to determine the covariance of the corresponding bands among two imagery sets. The selection of priors is further discussed in Section III-C.

B. Temporal Interpolation: Bayesian Inference

After obtaining the synthetic narrow band spectra of the multispectral observations, the Bayesian inference is utilized to interpolate along the temporal dimension to create the STRS. The method infers a vector of true spectral reflectance factors \(x\) from a number of noisy observations \(y\). The mathematical formulation is set up as a linear Gaussian system (8)

\[
y = Ax + \epsilon
\]

\[
\epsilon \sim N(0, \sum_y), \quad \sum_y = \sigma_y^2 I
\]

where \(A\) is a logical \(N \times D\) matrix of the \(N\) number of observations and \(D\) is the length of the date vector which will be interpolated. This matrix \(A\) is used to select the dates for which images are available images. The noise is assumed to have normal Gaussian distribution (9) with a mean value of 0 and the distribution equal to the observation noise, or sensor precision \((\sigma_y^2)\) which is further multiplied by an identity matrix \(I\). The sensor precision is inversely related to the uncertainty and must be estimated by the user (see Section III-D).

The vector of true reflectance factors \(x\) is also defined as a Gaussian distribution (10). The temporal profile is assumed to be smooth, meaning that the value of \(x\) at date \(j\) is the average of its neighbors (11) altered by Gaussian noise (12)

\[
p(y|x) = N(\mu_y|x, \sum_x)
\]

\[
\mu_y|x = -L^T L x
\]

\[
\sum_x = (\sigma_x^2 L^T L)^{-1}
\]

\[
L = \frac{1}{2} \begin{pmatrix}
-1 & 2 & -1 \\
\vdots & \ddots & \vdots \\
-1 & 2 & -1
\end{pmatrix}
\]

where \(L\) (13) is a second-order finite difference matrix used to control the error term as a function of the discrepancy between neighboring observations [19]. \(\sigma_x\) can be used to control the smoothness of the interpolation. By assigning the prior data a higher precision than the precision of the observations \((\sigma_x > \sigma_y)\), the prior will have a higher weight in the interpolation, resulting in a smoother profile. Conversely, by assigning a relatively low \(\sigma_x\) \((\sigma_x < \sigma_y)\), the temporal interpolation will more closely follow the observed spectra [19]. The value of \(\sigma_x\) depends on the expected variability of the spectra over time, and may be determined empirically. Section III-D explains how \(\sigma_x\) was obtained in the current study.

III. METHODOLOGY

A. Study Area

The study area is a potato field at 51°19’00” N and 05°10’14” E, near the village of Reusel in The Netherlands. The average spectral reflectance with four levels of initial fertilization from 24 experimental plots \((13 \times 30\, \text{m})\) (Fig. 1) was obtained on a weekly basis between June 6, 2013 and August 23, 2013 (Table I). Six spectral measurements were taken per experimental plot using a Cropscan Multiplespectral Radiometer (MSR16R, Cropscan Inc.) which has 13 spectral bands in the VIS/NIR spectrum (Table I) [4]. At the same locations, an LAI-2000 Plant Canopy Analyzer was used to measure the LAI of potato plants and a Minolta SPAD-502 was used to obtain chlorophyll measurements after transforming SPAD values to chlorophyll concentrations using the relations described by [21]. More information regarding the experimental setup can be found in [21].

B. Image Pre-Processing

A hyperspectral system on an UAV consisting of a Specim ImSpector V10 2/3” spectrograph mounted on an Aerialtronics Altura AT8 octocopter was developed by the WU under the Smart Inspectors project [10]. This UAV was flown over the

Fig. 1. Study area consisting of 24 experimental plots under four different initial fertilization regimes over the Formosat-2 image on July 18th.
study area at four dates (Table I). All images were georeferenced, orthorectified, and atmospherically corrected using the empirical line calibration method [21].

Eight cloud-free Formosat-2 images were available over the study area during the 2013 growing season (Table I). The Formosat-2 imagery was geo-referenced and co-registered to the UAV imagery using a high-resolution aerial photograph. All imagery was converted to reflectance factors using the parameters in the Formosat-2 metadata files. Light and dark pseudo-invariant pixels were identified in the entire scene by selecting pixels with the least reflectance variation in all the images. These pixels were used to normalize all images to the reflectance of the June 6th Formosat-2 image. The Formosat-2 images were then clipped to the extent of the study area, and a radiometric normalization was applied between the Formosat-2 and UAV imagery. The UAV imagery taken between June 6th and July 17th were convolved to the Formosat-2 spectral bands using the Formosat-2 spectral response function [22] and radiometrically normalized.

The STRS in the current application was constructed at experimental plot level. Therefore, the average spectral reflectance of each experimental plot was calculated for all UAV and Formosat-2 images. Field reflectance measurements using the Cropscan MSR16R were also averaged for each experimental plot.

### C. Bayesian Imputation of Formosat-2 Spectra

*a priori* information regarding the spectra of endmembers within the scene was obtained by creating a spectral library listing all the UAV spectral reflectance factors in the four available images. The study area consists of a potato field where the endmembers within the image series range from soil to green vegetation at various growth stages. It is assumed that the surface spectra within the extent of the STRS are represented within the available UAV imagery. This spectral library was convolved using the Formosat-2 normalized spectral response curve to obtain four spectral “bands” comparable to the Formosat-2 reflectances.

For each experimental plot and each Formosat-2 image, the 100 UAV spectra with the lowest absolute difference to the Formosat-2 spectra were selected from the convolved spectral library. The average, standard deviation, and covariance were calculated for each of the hyperspectral UAV bands of these 100 samples, and used as the prior for the Bayesian imputation. Selecting the *a priori* information separately for each experimental plot allows the imputed spectra to represent spatial and temporal variation i.e., differences between plots with low vegetation growth and a closed canopy, allowing for a more accurate imputation.

### D. Spectral–Temporal Interpolation

Three STRSs were created to illustrate the added value of the proposed method. This first method is similar to the STRS methods studied by [18] and will be referred to as “Direct.” It applied a cubic-spline interpolation to the Formosat-2 and UAV observations, thus interpolating simultaneously along spectral and temporal dimensions. The second method, which will further be referred to as “Two-step,” first imputed the Formosat-2 spectra along the spectral dimension (as in Section II.A.) and then applied a spline interpolation along the temporal dimension. This is similar to [17], although they applied a spline interpolation along the spectral dimension rather than utilizing Bayesian imputation. In the current scenario, the Bayesian imputation is applied first, as differences in spectral characteristics between the two image sources is much larger than the ones in [17]. Third, the Bayesian STRS applied the method described in Section II, consisting of spectral imputation followed by temporal inference. The uncertainty of the Formosat-2 and UAV images ($\sigma_y$) was defined as the RMSE between the plot reflectances obtained from the imagery and those obtained from the field data on June 6th and July 17th. The prior uncertainty $\sigma_x$ was determined empirically by maximizing the correlation between the STRS resulting from a defined $\sigma_x$ to the field data on the same two dates.

One STR using each of the three methods was created for all 24 experimental plots. The optimized soil-adjusted vegetation index (OSAVI) (14) [24] and modified chlorophyll absorption in reflectance index (MCARI) (15) [24] were obtained from the STRS for all nine dates with corresponding field measurements. OSAVI is a structural index related to LAI, whereas MCARI is a hyperspectral index related to canopy biochemical parameters e.g., chlorophyll. Both of these have previously shown strong relations to yield variability [25].

\[
\text{OSAVI} = \frac{1.16 \times (\rho_{800} - \rho_{670})}{\rho_{800} + \rho_{670} + 0.16} \quad (14)
\]

\[
\text{MCARI} = \frac{(\rho_{700} - \rho_{670}) - 0.2 (\rho_{700} - \rho_{550})}{\rho_{700} / \rho_{570}} \quad (15)
\]

The correlations between the vegetation indices obtained from the STRSs and 1) the same vegetation index at field level; 2) the LAI measured at field level; and 3) the canopy chlorophyll measurements were calculated. A linear regression was constructed between the canopy chlorophyll field measurements and STRS MCARI values on corresponding dates. The coefficients obtained through these regressions were applied to the STRS to obtain daily canopy chlorophyll estimates.
The constructed STRSs were 4-D datasets providing daily vegetation spectra with 101 bands for each experimental plot. The STRS of experimental plot 1 using each of the three methods are presented in Fig. 2, while the rest of the plots obtained similar results which are not shown here. The limitations of the Direct method are demonstrated in Fig. 2(a). The last UAV image is on July 17th, whereas Formosat-2 imagery was still available for July 22nd and August 2nd. However, the Formosat-2 imagery only has spectral bands at 660 and 830 nm. The Direct method therefore “flattens” the spectra at the end of July, losing the characteristic red-edge of vegetation reflectance. This is also illustrated in Fig. 3(c).

The two-step method retains the traditional spectral characteristics of vegetation [Fig. 2(b)]. However, the temporal spline interpolation causes spectra to change rapidly in short time periods. For example, the Formosat-2 reflectance factors on July 8th and July 18th are lower than the UAV reflectance factors on July 5th and July 17th, respectively. The sharp decrease between the UAV and subsequent Formosat-2 observations causes the two peaks in green reflectance (∼560 nm) at these dates. In contrast, the new Bayesian STRS methodology presents realistic daily spectra with smoother temporal changes in Fig. 2(c).

The RMSE and r between the STRS and Cropscan data also indicate that the proposed Bayesian approach performs better than the other two methods (Table II). It is important to note that field data acquisition methods may partly explain discrepancies between STRS and Cropscan spectra. For example, on June 6th the potato plants were not fully grown, and the canopy was still open. The Cropscan apparatus was directed at the

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Direct spline</th>
<th>Impute + spline</th>
<th>Bayesian approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.047</td>
<td>0.039</td>
<td>0.032</td>
</tr>
<tr>
<td>r</td>
<td>0.923*</td>
<td>0.947*</td>
<td>0.953*</td>
</tr>
</tbody>
</table>

N = 2808, P < 0.001 marked by *.
potato plant, whereas the UAV and Formosat-2 images consist of mixed pixels and are influenced by the soil background. This explains why the UAV spectra, and consequently the STRS spectra are lower than the Cropscan data on this date [Fig. 3(a)]. These differences are no longer visible once the canopy has closed [e.g. Fig. 3(b) and (c)]. This discrepancy is especially important when using vegetation indices which are sensitive to soil background effects, e.g., red-edge position (REP).

The correlations between the OSAVI obtained through the STRS and the field data are similar for all three methods tested (Table III). The Direct method provides slightly higher correlations to the LAI and canopy chlorophyll than the Bayesian STRS, which could be due to an overestimation of the sensor uncertainties. Further research could analyze methods to estimate the uncertainty of satellite measurements. However, the MCARI obtained through the Bayesian approach has a higher correlation to LAI and canopy chlorophyll than the other two methods. This is likely due to the fact that the wavelengths which are utilized in the vegetation indices. The OSAVI is based on surface reflectance at 670 and 800 nm, which fall within the range of Formosat-2 spectral bands. The MCARI, however, utilizes surface reflectance data at 700 nm, which is not present in Formosat-2 imagery. It is therefore highly dependent on the interpolation method used. This is also evident in Fig. 4, which indicates that the Bayesian STRS method more accurately captures the crop phenological status represented by the canopy chlorophyll content based on the MCARI.

### V. Conclusion

This paper presents a new approach to construct a 4-D STRS, which contains continuous surface reflectance data along both spectral and temporal dimensions. The Bayesian STRS approach obtained a lower RMSE (0.032) and higher correlation (0.953) to spectral measurements at field levels than two alternative STRS methods based on previous studies [17], [18]. The new method also has a considerably more accurate estimation of MCARI, a vegetation index based on wavelengths outside the extent of Formosat-2 imagery. These findings are very important for future STRS applications, as it indicates that constructing an STRS based on the proposed Bayesian method can accurately interpolate a limited number of hyperspectral measurements to daily observations during an entire growing season. Future applications of STRS should consider that the increased precision of narrowband indices obtained from the STRS should compensate for the additional uncertainty induced by spectral–temporal interpolation techniques when compared to direct broadband observations—as is the case with canopy chlorophyll in the current study.

This study demonstrates the possibility of accurately combining multispectral and hyperspectral data, along both spectral and temporal dimensions through a Bayesian approach to STRS. Future studies could combine additional sensors, providing surface reflectance data at the spectral and temporal intervals defined by the user. In applications such as precision farming, it could help bridge the gap between sensor capabilities and data requirements.

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### References


