Simulation of Optical Remote Sensing Systems

JOHN P. KEREKES AND DAVID A. LANDGREBE, FELLOW, IEEE

Abstract—With the advent of the Eos era and of configurable sensors capable of gathering even more detailed data, users of these instruments are faced with the twin problems of specifying data acquisition parameters and extracting desired information from the voluminous data. To help in better understanding these problems, research has begun on understanding the remote-sensing process as a system and investigating the interrelated effects of various parameters.

A system model for the simulation of remote-sensing systems is presented. The system is divided into three parts: The scene, the sensor, and the processing algorithms. Models are presented and implemented for these various component systems. Validation of the system model is considered over a specific test site. Results of the simulation for various scene and sensor configurations are included.

Keywords—Remote-sensing system, image modeling, optical sensor modeling, remote-sensing experiment design.

I. INTRODUCTION

As both sensor systems and processing systems become increasingly complex and configurable, the need increases for understanding the interrelated impact of various system parameters on system performance. In many remote-sensing systems the design of the sensors has been done to satisfy a broad range of user communities. Designers were often forced to rely on trade-off studies of various components that were studied independently to reach an acceptable compromise in the system design. As we now enter the age of user configurable sensors, such as HIRIS [1] and MODIS [2], the design of the baseline system continues to need to satisfy a broad user base, but also guidelines need to be developed and be available to help the users in designing their experiments. Simulation of the system by using accurate computational models to investigate system parameter trade-offs represents one approach to this goal.

Others have used this approach to study prototypical sensing system components. A simulation program developed by the Environmental Research Institute of Michigan, reported in [3], provided a proprietary method of evaluating sensor designs. A study of particular sensor configurations and processing algorithms presented in [4] also used a simulation program. But these works were conceived with specific purposes in mind, and the published results were rather limited in scope and application.

The present work is intended to be flexible, and to provide a vehicle for exploring the intricacies of complete remote-sensing systems in the most general sense. A primary goal of this work is to understand the interrelated effects of parameter choices on the overall system performance. These results should be useful to further the development of the technology of remote sensing into a science.

The flexibility of the simulation approach also leads to the ability to generate simulated images, which are not possible to obtain at present. This provides a tool to create realistic HIRIS-type images and explore ways of processing and extracting information before actual images are possible. A simulation can also help in the design of experiments for current sensors as well as those in the MODIS/HIRIS era by obtaining an idea of the trade-offs involved in specifying various conditions of observation.

In this paper we present a model of remote-sensing systems with the goal of obtaining an increased understanding of the interrelated effects of system parameters. In the next section we discuss the scope of such a system and present the overall system model. This is followed by discussions of the models for the various parts of the system, including the definition, parameters, and examples of each model. Validation of the model is considered by comparing real and simulated images of an intensive study site. Results of applying the model to various system configurations using simulated Landsat sensors are then presented to show how the simulation can be used to investigate the interrelated effects of system parameters.

II. REMOTE-SENSING SYSTEM MODEL

The system model used in this research covers the entire remote-sensing process, starting with the scene, progressing through the sensor, and ending with a final output measure from the processing algorithms. Thus we are concerned with the overall process rather than the individual pieces. We use well-developed models of others in putting together the system model.

The research has centered around passive optical sensors (airborne or spaceborne) used in land resource analysis applications. Examples of these include the SPOT and Landsat sensor systems and the upcoming HIRIS instrument. The wavelength range considered has been 0.4–1.1 μm, although the models are valid throughout the entire reflective portion of the optical spectrum.
The scenes considered in this initial work have been of agricultural areas, with a goal of classifying the simulated images into the appropriate ground-cover classes. It is noted that the use of agricultural areas is particularly attractive for tool development. As compared to natural areas, agricultural areas characteristically have large areas (i.e., fields) for which at least the plant species is constant, thus greatly facilitating the process of quantitative performance evaluation. On the other hand, it is noted that, as compared to what one might at first imagine, such fields are usually by no means spectrally uniform, especially when one goes beyond simple species identification in terms of the information desired. Thus an emphasis in the system model on sources of variability that can influence the classification accuracy is nicely facilitated, and the logical extrapolation to system performance in non-cultured ground areas is facilitated.

Fig. 1 shows the overall structure of the remote-sensing system model used. This division of the system was described in our previous work [5] and was chosen to allow both fidelity and flexibility in the system simulation. Scene model parameters can be chosen appropriately for various types of scenes to be used, with a common interface to the sensor being a high-resolution scene file. This file contains a high spatial and spectral resolution discrete version of the spectral radiance function present at the input aperture of the sensor. A user-defined sensor then operates on this scene file to create a remotely sensed multispectral image. Specified processing algorithms are then applied to this multispectral image to obtain a resultant classification accuracy or similar output measure.

III. SCENE MODEL

A. Introduction

The task of the scene model is to accept a description of the scene and produce a high spatial and spectral resolution scene file consisting of the spectral radiance as seen by the sensor. By high spatial resolution, we mean scene pixel sizes several times smaller than those of the sensor. High spectral resolution means several spectral samples per sensor spectral band.

The scene model consists of two parts: The surface reflectance array, and the solar illumination and atmospheric effects process. Fig. 2 contains a block diagram of the scene model. The surface reflectance array consists of spectral reflectance vectors arranged spatially by class and derived from measurements made in the field. The illumination and atmospheric effects include the incident spectral irradiance on the surface, the spectral transmittance back up through the atmosphere, and the additive path radiance incident on the sensor aperture. The next two sections describe these parts in further detail.

B. Surface Reflectance Array

The modeling of remotely sensed scenes can indeed be very complex. In [6] the authors divide scene models into two groups: Those that are generally deterministic and based upon the geometry and reflectance of the surface cover, and those that are generally stochastic and derived from the statistics of the remotely sensed image.

The form of the surface reflectance models that can be implemented in our simulation may be quite general, but for now we have chosen a stochastic model based upon field spectral reflectance measurements and image spatial characteristics. The spectral reflectance vectors are generated according to a multivariate Gaussian distribution, while the spatial characteristics are included in the reflectance array by a two-dimensional autoregressive (AR) model. This model is described by (1) for each wavelength and for a scene with X columns and Y rows. Wavelength-to-wavelength spatial correlation is assumed to be zero at this point:

\[
r(x, y) = C_1 r(x - 1, y) + C_2 r(x, y - 1) \\
+ C_3 r(x - 1, y - 1) + \sigma_z(x, y)
\]

\(\forall x, y \in X, Y\)

(1)

where

- \(r(x, y)\) reflectance in one wavelength band, at column \(x\), row \(y\),
- \(x, y\) high-resolution spatial column, row index in scene,
Fig. 2. Scene model block diagram.

\[ C_1, C_2, C_3 \] spatial AR model parameters,
\[ \sigma_u \] standard deviation of Gaussian driving process, computed to retain unit variance for \( r \),
\[ z(x, y) \] independent Gaussian random numbers with unit variance and zero mean.

The initial conditions of the first row and column are set to zero. Table I shows typical values of the spatial parameters for a variety of scene types computed from an image band of the near infrared.

The surface reflectance array of spectral reflectance vectors \( P(x, y) \) is generated in several steps: First we define a size for the scene and a ground cover class for each pixel in the scene. Then spatially correlated but spectrally uncorrelated unit variance reflectance arrays are created by using (1) with the appropriate spatial parameters for each class and for each of the \( M \) wavelengths and arranged as \( M \times 1 \) spectral vectors \( R(x, y) \) having an identity spectral covariance matrix. Reflectance data of each class \( k \) is obtained and the mean spectral reflectance vector \( \bar{P}_k \) and covariance matrices \( \Sigma_k \) are computed. The eigenvalues and eigenvectors of these covariance matrices are then computed and arranged as matrices \( \Lambda_k \) and \( \Phi_k \), respectively. The final surface reflectance array is then computed by (2), using the appropriate class statistics for each scene pixel:

\[ P(x, y) = \bar{P}_k + \Phi_k \Lambda_k^{1/2} R(x, y). \] (2)

The reflectance statistics used in this model are obtained from a database of over 200,000 spectral reflectance measurements made at the Laboratory for Applications of Remote Sensing (LARS) over the years. These measurements were made with a 20 nm or less spectral resolution over the reflective portion of the optical spectrum and under a variety of laboratory and field conditions. See [7] and [8] for more information.

The ground size in meters of the scene pixel elements is denoted by \( G_x \) for the across-scene pixel size, and by \( G_z \) for the down-scene pixel size. These parameters, along with the number of row and columns in the scene and the sampling interval of the sensor, define the size of the resulting image.

The simulation program is currently setup for the scene reflectance to be computed in \( \Delta \lambda = 10 \text{ nm} \) increments from 0.4–1.1 \( \mu \text{m} \). This results in \( M = 71 \) samples across the range. Thus the covariance matrices \( \Sigma_k \) will be 71 by 71, and the mean vectors \( \bar{P}_k \) will have a dimension of 71 also. In computing the eigenvalues of this covariance matrix, one obtains only 10–15 eigenvalues of any significance. This indicates that the intrinsic dimensionality of the reflectance process may indeed only be 10–15, a factor used in the spectral compression scheme, which is available in our simulation and described by [9].

### C. Solar Illumination and Atmospheric Effects

The atmospheric simulation program LOWTRAN 7 [10] was chosen for the atmospheric model because of its high spectral resolution of 20 cm\(^{-1}\) and its ability to calculate scattered radiance. This latest version of LOWTRAN includes multiple scattering in its calculations.

While LOWTRAN can compute reflected ground radiance and scattered path radiance in one call, this can only be done by assuming a constant surface albedo. Rather than modify the program, we use four separate calls to LOWTRAN. The program is used to compute the direct solar spectral irradiance \( E_{\lambda, Direct}(V_{\gamma}, \theta_{solar}) \) at the surface, the atmospheric spectral transmittance \( T_{\lambda, Atm}(V_{\gamma}, \theta_{view}) \) for the path from the surface to the sensor, and two calls for the scattered spectral path radiance \( L_{\lambda, Path}(V_{\gamma}, \theta_{solar}, \theta_{view}, \phi_{solar}, \phi_{view}) \), once for an albedo of 0 and once for an albedo of 1.0. These two calls for the path radiance allows for a pixel surface reflectance dependence by linearly interpolating between these extremes. The path spectral radiance for the wavelength index \( m \) at location \( x, y \) is calculated as in (3). Here, \( \rho_{\text{ext}}(x, y) \) is the \( m \)-th element at location \( x, y \) of the surface reflectance array vectors \( P(x, y) \):

\[
L_{\lambda, Path}(x, y, m) = L_{\lambda, Path}^{\text{direct}}(m) + \rho_{\text{ext}}(x, y) \\
\cdot [L_{\lambda, Path}^{\text{direct}}(m) - L_{\lambda, Path}^{\text{direct}}(0)].
\] (3)

Thus LOWTRAN computes these quantities once per scene, and the resulting spectral radiance is computed across the scene by applying these quantities to the surface reflectance array. Table II defines the atmospheric and goniometric parameters used in the simulation. The 1976 U.S. Standard atmosphere model is used along with a rural extinction haze. Other LOWTRAN parameters are set to default values.

Since many remote-sensing experiments describe atmospheric quality with the spectral optical thickness \( \tau_{\lambda} \), an empirical relationship was developed from data in [11] and [12] to relate this parameter to the surface meteorological range. This relationship is presented in (4), and is assumed to be valid over the wavelength range of interest:

\[
\tau_{\lambda}(V_{\gamma}, \theta_{\text{solar}}) = 1.35 \sec(\theta_{\text{solar}}) \lambda^{-1.328} V_{\gamma}^{-0.656}.
\] (4)

Another empirical relationship was developed from data in [13] to compute an estimate of the total (direct and dif-
fuse) spectral irradiance \( E_{\lambda, \text{Total}}(V, \theta_{\text{sol}}) \), occurring at the surface. This relationship gives the total spectral irradiance as a function of the direct spectral irradiance and the spectral optical thickness and is described by the following:

\[
E_{\lambda, \text{Total}}(V, \theta_{\text{sol}}) = \frac{\cos(\theta_{\text{sol}})}{\exp\left[-1.26 \tau_{\lambda}(V, \theta_{\text{sol}})\right]} E_{\lambda, \text{Direct}}(V, \theta_{\text{sol}}). \tag{5}
\]

Note that this equation includes wavelength dependence through the spectral optical thickness and the direct spectral irradiance. The spectral radiance seen by the sensor at any particular scene location is then described by

\[
L_{\lambda, \text{Sensor}}(x, y, m) = \frac{1}{\pi} \left[ E_{\lambda, \text{Total}}(m) \rho_{\lambda}(x, y) T_{\lambda, \text{Atm}}(m) \right] + L_{\lambda, \text{Path}}(x, y, m). \tag{6}
\]

We assume the surface reflectance to be Lambertian, and the total spectral irradiance and atmospheric transmittance to be constant across the scene.

IV. SENSOR MODEL

A. Overview of Sensor Model

The sensor model transforms the scene spectral radiance file into a multispectral digital image of the scene. Fig. 3 shows the block diagram of the sensor model. The model first applies the spectral response by integrating each band’s response across the scene spectral range, and then applies the spatial response of the sensor by the discrete convolution of separable line spread functions in the two spatial dimensions. Next, noise is added to the resulting image before band scaling is applied, and the final conversion to quantized levels occurs based on the number of radiometric bits. Table III shows the sensor model parameters.

While other sensor effects could be included in this model, we have chosen for now to limit the complexity of the model.

B. Spectral Response

The resulting array \( e(x, y, l) \), after the spectral response is applied to the spectral radiance of the scene as received by the sensor \( L_{\lambda, \text{Sensor}}(x, y, m) \), is computed as follows:

\[
e(x, y, l) = \Delta\lambda \sum_{m=1}^{M} L_{\lambda, \text{Sensor}}(x, y, m) \cdot s_l(m) \tag{7}
\]

where \( x, y \) are pixel locations in the scene radiance file, \( m \) is the wavelength index of the scene file, and \( l \) is the band index of the image. In the generation of HIRIS type images, the image spectral resolution is the same as the scene, and this operation is replaced by a direct multiplication of the sensor response at each wavelength.

C. Spatial Response

Before the spatial response is applied the sensor sampling intervals and locations are modified by the sensor viewing geometry. That is, they are rotated by the viewing azimuth angle \( \phi_{\text{view}} \), and scaled by the cosine of the viewing zenith angle \( \theta_{\text{view}} \). A viewing azimuth angle of 0° is assumed to be from the top center of the scene, i.e., north on a map. This is shown in (8) and (9):

\[
\begin{bmatrix}
\Delta W' \\
\Delta Z'
\end{bmatrix} =
\begin{bmatrix}
\cos(\phi_{\text{view}}) & \sin(\phi_{\text{view}}) \\
-sin(\phi_{\text{view}}) & \cos(\phi_{\text{view}})
\end{bmatrix}
\begin{bmatrix}
\Delta W \\
\Delta Z
\end{bmatrix}
\tag{8}
\]

\[
\begin{bmatrix}
\Delta U' \\
\Delta V'
\end{bmatrix} =
\begin{bmatrix}
\cos(\phi_{\text{view}}) & \sin(\phi_{\text{view}}) \\
-sin(\phi_{\text{view}}) & \cos(\phi_{\text{view}})
\end{bmatrix}
\begin{bmatrix}
\Delta U \\
\Delta V
\end{bmatrix}
\tag{9}
\]

The spatial response is then applied to each band to obtain the resulting image radiance array \( b(i, j, l) \) as in
(10). The pair \((i, j)\) denote the column, row pixel location in this image radiance array:

\[
b(i, j, l) = \frac{G_s G_x}{(A_i, \Delta U'H)(A_i, \Delta V'H)} \sum_{\sigma_P=1}^{O+1} \sum_{p=1}^{P+1} \exp(i \Delta W'H + o \Delta U'H) \\
\frac{1}{G_s} \exp(j \Delta Z'H - p \Delta V'H) \\
h_t \left( \frac{o \Delta U'H}{G_s} \right) h_s \left( \frac{p \Delta V'H}{G_s} \right).
\] (10)

Here, \(O+1\) and \(P+1\) represent the number of coefficients in the across-scan and down-track line-spread functions, respectively, and \(h_t\) and \(h_s\) contain the maximum response. Note that since the scene radiance array has discrete pixel locations, all index quotients are rounded to the nearest integer. Also, at the edges, the extreme row or column is repeated as necessary to allow for the complete application of the spatial response.

The spatial response is implemented as an array in the simulation to allow for nonsymmetric and nonanalytic response functions. A typical spatial response of the Landsat sensors is shown in Fig. 4. This example is for the Landsat 5 Thematic Mapper instrument flown at an altitude of 705 km and is taken from [14].

D. Noise Model

After the spectral and spatial responses have been applied, shot and thermal noise is then added by the use of random number generators \(n_1(\cdot), n_2(\cdot)\), which are zero mean unit variance Gaussian, and the calibration error by using the random number generator \(u(\cdot)\), which is uniform \((-0.5, +0.5)\). These random numbers are scaled by the appropriate standard deviation multipliers and added to the radiance array to produce the noisy image \(f(i, j, l)\), as in the following:

\[
f(i, j, l) = [b(i, j, l) + \sigma_r(l) n_1(i, j) + \sigma_o n_2(i, j) b(i, j, l)] \\
\cdot [1 + \sigma_c(l) u(i, j)].
\] (11)

For example, typical values for the thermal and shot noise levels for the first four bands of the Landsat Thematic Mapper instrument were obtained from [15] and are shown in Table IV. Reference [16] considered the effect of these sources of noise on classification accuracy and has been used in the development of our present work. The calibration error levels are assuming a 1 percent of value relative error between detectors due to the changing of their sensitivity and/or calibration inaccuracies.

Fig. 4. The across-scan (solid line) and down-track (dashed line) spatial response of the Landsat 5 TM instrument (from reference [14]).

<table>
<thead>
<tr>
<th>Band</th>
<th>(\sigma_t(l)/\sigma_{FWR}^2)</th>
<th>(\sigma_o(l)/\sigma_{FWR}^2)</th>
<th>(\sigma_c(l)/\sigma_{FWR}^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.008</td>
<td>0.009</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>0.005</td>
<td>0.006</td>
<td>0.01</td>
</tr>
<tr>
<td>3</td>
<td>0.004</td>
<td>0.007</td>
<td>0.01</td>
</tr>
<tr>
<td>4</td>
<td>0.004</td>
<td>0.003</td>
<td>0.01</td>
</tr>
</tbody>
</table>

*The thermal and shot noise levels are taken from reference [15].

E. Scaling and A/D Conversion

The noisy image is then scaled by the full-scale radiance for that band in preparation for the A/D conversion. The published full-scale radiances for the Landsat instruments assume a uniform unit response over the nominal bandwidth. In practice, the instruments do not possess such a response. Fig. 5 shows the measured average Landsat 4 MSS spectral response for band 4 as given in [17].

The calibration of the actual instruments is done by assuming a unit response across the nominal bandwidth, so in order to scale the simulated radiances appropriately, a normalizing factor \(N(l)\) is computed for each band \(l\) to relate the nominal full-scale radiance to the actual full-scale radiance. This factor is the ratio of the effective bandwidth of the band response to the nominal bandwidth, as computed as follows:

\[
N(l) = \frac{\Delta \lambda \sum_{m=1}^{M} s_i(m)}{\text{Nominal Bandwidth of Band } l}.
\] (12)

For the example given in Fig. 5, the nominal bandwidth is 0.3 \(\mu m\), while the effective bandwidth is only 0.179 \(\mu m\), resulting in \(N(4)\), shown as follows:

\[
N(4) = \frac{0.179}{0.300} = 0.597.
\] (13)
The radiance values are scaled and converted to a digital number as in (14), producing the multispectral image \( d(i, j, l) \):

\[
\begin{align*}
    d(i, j, l) &= \text{nearest integer} \left\{ \frac{f(i, j, l)}{N(l) \cdot L_{\text{full}, l}} \right\} \\
    &= \left\{ \frac{1}{2} \left( \left[ \frac{f(i, j, l)}{N(l) \cdot L_{\text{full}, l}} \right] + 1 \right) \right\}.
\end{align*}
\]

This model is extremely flexible; any spatial and spectral response can be used, since they are defined by arrays. Also, different noise mechanisms may be simply inserted into the signal chain as they may be appropriate.

Sensors that have been implemented in this simulation include Landsat MSS and TM (first four bands only), SPOT, various aircraft scanners, and a hypothetical spaceborne imaging spectrometer named HIVNIR, with a 10-nm spectral resolution from 0.4 to 1.0 \( \mu \text{m} \) and the spatial resolution of Landsat 5 TM.

V. PROCESSING MODEL

A. Overview

The task of the processing portion of the simulator is to take the multispectral image from the sensor and any other user-defined input data or algorithms and then compute an output measure; e.g., class separability or classification accuracy. At present, the model used in the simulation includes three aspects of processing: 1) Spectral feature compression for high dimensional images (optional); 2) multiclass separability measures computed over designated class boundaries; and 3) classification accuracy based upon a Maximum Likelihood (ML) classifier using defined training areas. Since the user defined the original scene, a classification accuracy can be computed directly.

Fig. 6 shows the block diagram of the processing portion of the simulator.

B. Spectral Feature Compression

The spectral feature compression method [9] uses features derived from the eigenvectors of the covariance matrix of typical surface cover reflectance measurements to transform the high dimensional image vectors of such imaging spectrometers as AVIRIS or HIRIS to a lower dimensional space, while retaining the interclass separability necessary to perform classifications. This processing algorithm can be implemented only when the sensor is the HIVNIR described in the last section.

C. Separability Output Measure

Separability measures have been shown to provide an indication of classification accuracy [18]. Several are implemented in the simulation to give an indication of classification accuracy without the added computer time of performing the actual classification.

A multiclass separability measure can be obtained from a priori class probability weighted pairwise summations of the two-class separability measure transformed Bhattacharya distance [19]. Also in this simulation we use a multiclass separability measure described in [20] which depends on the class mean vectors and covariance matrices by weighting them according to a priori probabilities. This measure \( J_F \) is the trace of the product of the inverse of the within-class scatter matrix \( S_w \) and the between-class scatter matrix \( S_b \), as shown as follows:

\[
J_F = \text{tr} S_w^{-1} S_b
\]

where

\[
S_w = \sum_{k=1}^{K} P_k S_k, \quad S_b = \sum_{k=1}^{K} P_k (\overline{d}_k - \overline{d}_o) (\overline{d}_k - \overline{d}_o)^T
\]

\[
\overline{d}_o = \sum_{k=1}^{K} P_k \overline{d}_k.
\]

In these equations, \( P_k \) is the a priori probability of class \( k \), \( \overline{d}_k \) is the mean vector of class \( k \) computed from the image, and \( S_k \) is the covariance matrix for class \( k \). All of the separability measures are computed over a defined area of the image within each ground-cover class.

D. Classification Accuracy

The ML classifier uses the standard Gaussian assumption with class a priori probabilities dependent upon the numbers of pixels in each class. Since the scene is defined by the user, the class boundaries are known in the image and a classification accuracy can be computed directly. Class statistics are computed from designated training areas. The classification can be done on the original image or on the compressed image if the sensor was an imaging spectrometer type.
VI. MODEL VALIDATION AND RESULTS

A. Introduction

In the use of any model, one must have confidence in the structure and performance of the model as compared to the original system. By the nature of our model's construction we have confidence in its representation of the structure of the remote-sensing process. We explored the performance of the model in assessing the radiometric validity and in its application to the study of the interrelated effects of several parameters.

B. Radiometric Validation

To obtain confidence in the radiometric validity of the model, we obtained a data set of Landsat imagery over a test site for which surface spectral reflectance data was available. The values generated by the simulation could then be compared to the values of the real images.

A test scene was defined based upon data from an intensive study site in South Dakota [21]. As part of this program reflectance data, aircraft imagery, photography, and Landsat MSS passes were obtained. The details of this data set are given in Table V.

A particular area within this intensive study site was used to validate the simulation model and explore system trade-offs of various parameters. The area was chosen for its large uniform fields, each measuring approximately one-half mile by one-half mile. Fig. 7 shows a diagram of this particular area.

The reflectance data over these four fields were obtained by comparing the FSS radiances to those of a calibration plate with a known reflectance. The spectral reflectance factor was then converted from the 20-nm wavelength spacing of the FSS to the 10-nm resolution used in the simulator through a simple interpolation algorithm. For each of the four fields, the mean reflectance vector and covariance matrix (along with its eigenvalues and eigenvectors) was computed. Spatial parameters for the fields were estimated from the airborne scanner imagery. Other relevant data from the approximate time of the observations were obtained and are shown in Table VI.

A simulated scene was then created and a multispectral image was generated by the application of a simulated Landsat 2 MSS. Since an actual comparison of the real and simulated digital counts can be misleading and dependent upon the calibration levels used in the instrument, a conversion was also made to radiance values received by the instrument. Reference [22] contains conversion constants for Landsat 2 valid for the time of observation. Table VII shows the results. Radiance levels are mW/(cm²-sr).

Several sources of error may explain these discrepancies. Since many of the simulated values were lower than the actual ones, one or more of the contributions to the received radiance may be underestimated, including the diffuse ground irradiance, surface reflectance, or additive path radiance. Other sources of error could include a pos-

---

Fig. 7. Layout of four-field area of Hand County, South Dakota. No reflectance data was obtained over the farmstead in field 289 and it was left out in the simulation of the area.

### TABLE V

**Data Set for Hand County, South Dakota, Obtained on July 26, 1978**

<table>
<thead>
<tr>
<th>LandSat 2 Multispectral Scanner</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Channels</td>
</tr>
<tr>
<td>Scene</td>
</tr>
<tr>
<td>Altitude</td>
</tr>
<tr>
<td>Ground Size ofIFOV</td>
</tr>
<tr>
<td>Time</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Aircraft Multispectral Scanner</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Channels</td>
</tr>
<tr>
<td>Altitude</td>
</tr>
<tr>
<td>Ground Size ofIFOV</td>
</tr>
<tr>
<td>Time</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Helicopter Field Spectrometer System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral Channels</td>
</tr>
<tr>
<td>Altitude</td>
</tr>
<tr>
<td>Ground Size ofFOV</td>
</tr>
<tr>
<td>Time</td>
</tr>
</tbody>
</table>

### TABLE VI

**Scene Conditions at Time of Observations**

- Meteorological Range (V₀): 31 Km
- Solar Zenith Angle (θSolar): 39°
- Solar Azimuth Angle (φSolar): 119°

### TABLE VII

**Comparison of the Radiance Values Between Real Landsat 2 MSS and the Simulated Image**

<table>
<thead>
<tr>
<th>Field</th>
<th>FSS Reflectance</th>
<th>MSS Average Digital Count</th>
<th>Landsat Radiance</th>
<th>Simulated Radiance</th>
<th>Percent Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>290</td>
<td>0.063</td>
<td>21.5</td>
<td>0.512</td>
<td>0.527</td>
<td>+2.9</td>
</tr>
<tr>
<td></td>
<td>0.083</td>
<td>26.9</td>
<td>0.421</td>
<td>0.405</td>
<td>-8.1</td>
</tr>
<tr>
<td></td>
<td>0.105</td>
<td>44.2</td>
<td>0.365</td>
<td>0.356</td>
<td>-2.9</td>
</tr>
<tr>
<td></td>
<td>0.200</td>
<td>20.7</td>
<td>1.386</td>
<td>1.323</td>
<td>-4.6</td>
</tr>
</tbody>
</table>

| Field | 108             | 0.068                      | 23.7             | 0.556             | 0.549         | -1.3 |
|       | 0.088           | 31.0                      | 0.475            | 0.475             | 0.0          |
|       | 0.121           | 36.8                      | 0.483            | 0.431             | -10.8        |
|       | 0.182           | 16.8                      | 1.111            | 1.020             | -8.3         |

| Field | 398             | 0.058                      | 22.1             | 0.524             | 0.505         | -3.6 |
|       | 0.078           | 27.6                      | 0.430            | 0.435             | +1.2         |
|       | 0.143           | 43.2                      | 0.457            | 0.449             | -16.8        |
|       | 0.208           | 20.1                      | 1.322            | 1.156             | -12.5        |

**Field 289**

| Band 1 | 0.043       | 18.3           | 0.448            | 0.439             | -2.0         |
| Band 2 | 0.031       | 14.8           | 0.256            | 0.250             | -2.4         |
| Band 3 | 0.252       | 66.1           | 0.620            | 0.623             | +0.6         |
| Band 4 | 0.388       | 36.6           | 2.317            | 2.394             | -3.4         |

*The mean surface reflectances are included in the table for comparison to the simulated radiances. The overall average difference between the Landsat and simulated radiances is 4.9 percent.*
sible 5 percent of value error in the calibration of the reflectance measurements [23], inaccurate specification of the surface meteorological range, undetected presence of thin high-altitude clouds, or inaccurate calibration of radiance as received by the satellite.

While the exact values were unable to be obtained, the simulation gave reasonably consistent values, and in this research the variation between the bands and the fields is more important than the exact values. The simulated values can only be as good as the reflectance (and specification of system parameters) used, and in this sense the simulator is accurate in reflecting the difference between the class reflectances. It is recognized that the simulation program will never be able to exactly duplicate the real situation, but by being able to reasonably well simulate the radiance values of a real situation, confidence is gained in the completeness of the system model.

C. Parameter Interrelationships

Next, a series of experiments were performed to investigate the interrelationships of several of these parameters. The scene as defined in Section VI-B was used as the starting point for the various experiments. In each of the experiments the classification accuracy is the average of the four individual accuracies. Also, these results are the average of five runs of the simulation to reduce the effects of the random number generators.

Two experiments were performed to explore the role of goniometric effects in the classification accuracy. One with the sensor looking straight down and the sun varying, and the other with the sun at zenith and the sensor increasing its viewing angle. The results are shown in Fig. 8. Note that these results were obtained while assuming Lambertian surface reflectance characteristics. Since the surface reflectance did not change with the zenith angle in this experiment, the variation in the results most likely came from the effect of the atmosphere and geometry involved. The effect of the sun zenith angle increasing was a consistently decreasing classification accuracy, while the increasing view zenith angle shows a flat spot for $\theta_{\text{view}} = 15^\circ$, $30^\circ$, and $45^\circ$.

This flat spot is most likely due to two offsetting effects: As the view angle increases, there is a decreased signal radiance and increased path radiance resulting in a lower classification accuracy. But at the same time the number of high-resolution scene pixels within the sensor IFOV increases, thereby decreasing class variation and resulting in a higher classification accuracy.

Another experiment was performed to illustrate how the effect of the atmosphere relates to the sun angle. For this experiment the sensor was again the Landsat MSS at $0^\circ$ zenith angle. Fig. 9 shows the result.

While the atmosphere does indeed have a detrimental effect for all sun zenith angles, it can be seen that the effect is significantly more pronounced for lower sun angles. The decrease in accuracy at low meteorological ranges is due to the reduced signal levels and increased shot noise due to path radiance, along with the high quantization error of the 6-bit radiometric resolution.

Next, an experiment was performed to see how the radiometric resolution affected classification accuracy for various types of sensors. In addition to the Landsat MSS sensor used above, also used were the Landsat TM, SPOT MSS, and HIVNIR defined earlier. Fig. 10 shows the results using a 10-km meteorological range. Here it appears that accuracy doesn't improve significantly at radiometric resolutions greater than 7 or 8 bits. This is due to the fact that above this resolution the other sources of error domi-
inate the quantization error and limit the classification accuracy. In addition to the spatial and spectral band differences, the absolute level of classification accuracy for the various sensors may be related to the noise levels used in the simulation. For the other instruments the noise levels were set similar to the ones described earlier for the Thematic Mapper.

VII. Summary and Conclusions

We have presented a system model for the study of the interrelated effects of parameters in optical remote-sensing systems. This model is aimed toward studying these effects on the ability of the system to distinguish between ground-cover classes. In this model we use field reflectance measurements, measured instrument responses and parameters, and well-developed models to replicate the real system as accurately as possible.

The radiometric validation of the model was considered by comparing the radiances received by an actual sensor to those produced by our simulator from field reflectances. Our simulated values were generally 5–10 percent below those of the real system, indicating a possible underestimation of the diffuse surface irradiance or the scattered-path radiance incident on the sensor. Uncertainties in the calibrations used for the comparison make it difficult to precisely state the error observed. However, since we are mostly concerned about relative class differences rather than absolute values, we believe the simulation model to be more than adequate for the goals of the research.

We have also presented some initial results of applying the remote-sensing system simulation to the study of varying system configurations for current Landsat-era sensors. While these results may indicate trends resulting from changing the system parameters, their veracity should not be accepted in the absolute. It must be stressed that these results are for a particular system model. But hopefully, they do illuminate relationships among the parameters and illustrate the potential applications of such detailed simulations.

The simulation model is currently being extended to include the entire spectral range of the HIRIS instrument. We are implementing a detailed model of that sensor and studying the effect of system parameters on signal-to-noise ratios and classification accuracy using various compression schemes. The results of this study will be presented in a future paper.

This ability to generate realistic HIRIS-type images will lead to many potential applications of the simulation program in the Eos era. Simulated HIRIS images could be generated by using the reflectance of healthy vegetation with pockets of stressed areas, and the ability of HIRIS to detect these areas could be studied under a variety of scene conditions. The simulation program could also be used to generate scenes of geological interest and investigate the sensitivity to system parameters of the identification of a few pixels with the kaolinite doublet. Agronomy applications include studying the effect of the atmosphere and the HIRIS sensor in determining soil characteristics with a detail previously not possible from space. These and many other applications are currently being considered for study.

Acknowledgment

This work was performed at the Laboratory for Applications of Remote Sensing (LARS) at Purdue University. The authors would like to thank L. L. Biehl of LARS for his assistance in obtaining the reflectance and image data used in these investigations. Acknowledgment is also given to the reviewers for their helpful suggestions in the preparation of this manuscript.

References


John P. Kerekes was born in South Bend, IN. He received the B.S.E.E., M.S.E.E., and Ph.D. degrees from Purdue University, West Lafayette, IN, in 1983, 1986, and 1989, respectively.

From 1983 to 1984 he was a member of the technical staff of the Space and Communications Group of the Hughes Aircraft Co., El Segundo, CA, where he performed circuit design for communications satellites. From 1984 to 1989 he was a Graduate Teaching Assistant in the School of Electrical Engineering at Purdue University. From 1986 to 1989 he was a Graduate Research Assistant, working with both the School of Electrical Engineering and the Laboratory for Applications of Remote Sensing. He is presently employed by the Massachusetts Institute of Technology Lincoln Laboratory, Lexington.

Dr. Kerekes is a member of Phi Kappa Phi, Tau Beta Pi, and Eta Kappa Nu.

David A. Landgrebe (S’54–M’57–SM’74–F’77) received the B.S.E.E., M.S.E.E., and Ph.D. degrees from Purdue University, West Lafayette, IN.

He is Professor at Electrical Engineering and Graduate Coordinator for the School of Electrical Engineering at Purdue University. His area of specialty in research is communication science and signal processing, especially as applied to Earth observational remote sensing. His research contributions to that field have been in the areas of multispectral pattern recognition, spectral spatial temporal classifiers, spectral feature design, and system simulation. He is also co-author of the text, Remote Sensing: The Quantitative Approach, and a contributor to the book, Remote Sensing of Environment, and the ASP Manual of Remote Sensing (1st ed.). He has been a member of the editorial board of the journal Remote Sensing of Environment since its inception, and is also on the editorial board of the journal Image and Computer Vision.

Dr. Landgrebe is a member of the American Society of Photogrammetry and Remote Sensing, the American Association for the Advancement of Science, and the American Society for Engineering Education. He is also a member of the Eta Kappa Nu, Tau Beta Pi, and Sigma Xi honor societies. He has received both of the outstanding teacher awards given by his department. He has also received the NASA Exceptional Scientific Achievement Medal for his work in the field of machine analysis methods for remotely sensed Earth observational data. He was President of the IEEE Geoscience and Remote Sensing Society during 1986 and 1987 and has been a member of its Administrative Committee since 1979.