Evaluation of an uncalibrated agricultural land model at the sub-field scale

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Evaluation of an uncalibrated agricultural land model at the sub-field scale

by

Jason Carl Patton

A thesis submitted to the graduate faculty
in partial fulfillment of the requirements for the degree of
MASTER OF SCIENCE

Major: Agricultural Meteorology

Program of Study Committee:
Brian K. Hornbuckle, Major Professor
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Iowa State University
Ames, Iowa
2010
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An uncalibrated agricultural land surface model, Agro-IBIS, was validated at the sub-field scale using data collected at a local agricultural field site planted with maize in 2009, with a focus on capturing the spatial variability and accumulation rates of soil moisture and leaf area index. Capturing the variability was deemed important for evaluating the model’s potential for inclusion as the land surface model in atmospheric models. An ensemble method of forcing the model with different combinations of input data was used in an attempt to produce the variability seen in measurements across the field. The model was able to produce a range of soil moisture similar to the range observed at the field site, though rates of soil water accumulation and drainage were much higher than observed. The spread in leaf area index measurements was not captured by the model, though the rate of leaf area accumulation was similar in both the field and the model. The model emerged the crop too early due to the lack of calibration, which led to a positive bias in leaf area. The bias in leaf area led to biases in a number of other variables, including sensible heat flux and in-canopy temperature. Despite the biases, which were expected due to the lack of calibration, the ability of Agro-IBIS to capture spatial variability in soil moisture at the sub-field scale make it a good candidate for coupling to other models.
CHAPTER 1. INTRODUCTION

1.1 Motivation

The advancement of most human societies from hunter-gatherer-based to agriculture-based has allowed many people, particularly those living in industrialized regions, to free themselves from the constant search for food and shelter and to focus on endeavors of science, technology, and art. As most societies are ill-equipped to return to the former hunter-gatherer state, it is imperative that agriculture be sustained until other efficient methods of providing food to the global community are discovered. However, food providers, and societies in general, are facing many challenges to their lifestyles, including a changing climate, degrading water quality, and greater energy demands. In order to continue living with the freedom agriculture provides us, we must learn how to face these challenges, or avoid them altogether. A better understanding of how agriculture affects soil, water, and climate (and in return, how each affects agriculture) is thus necessary so that we may make rational and sufficient policy and lifestyle changes to adapt to or mitigate the problems that stand before us.

1.1.1 Agriculture and Climate

One of the major factors that determine where vegetation, including crops, grows or has the ability to grow is climate (Prentice et al., 1992; Foley et al., 2003). While the climatic constraint on vegetation is well understood, many people do not realize that an opposite relationship also holds; vegetation itself is a factor in determining regional and global climates (Bonan, 1997; Foley et al., 2003). This relationship results from the surface of the Earth being a source or sink of heat, moisture, friction, and trace gases to the atmosphere. Compared to a bare soil surface, vegetation affects these important atmospheric boundary conditions by:
• increasing the solar radiation absorbed (i.e. decreasing albedo) at the surface.

• supplying extra moisture to the atmosphere from below the soil surface via transpiration.

• modifying the roughness of the surface; and

• storing carbon dioxide (CO$_2$), an important trace gas in determining the global surface temperature (i.e. a “greenhouse gas” or GHG), via photosynthesis.

The above list (summarized in Figure 1.1) is certainly not exhaustive, but should give one a general idea of how vegetation feeds back to the atmosphere and why it is important to consider changes in land use when discussing changes in climates.

![Figure 1.1 Summary of feedbacks between climate and vegetation, from Foley et al. (2003), with modifications.](image)

Compared to the rate of natural ecological succession, humans have modified the surface of the Earth at a drastic pace. The last 300 years alone have seen the conversion of 18 million km$^2$, or 12% of the Earth’s land surface, of naturally vegetated land to cropland, pasture, or urban use by humans (Ramankutty and Foley, 1999). An example of how this conversion has affected
climate is the change in suitability of the land for growing food (Ramankutty et al., 2006, Figure 1.2). An interesting irony seems to have developed, where by converting regions to croplands (e.g. central U.S.), we have reduced the suitability of some regions for growing crops. However, it is important to remember that suitability here is based on climate, not on soil type, land availability, etc.

Studies of land surface-climate feedbacks at the regional scale have highlighted more specific impacts of converting natural vegetation to croplands. Bonan (1999, 2001) has shown that the drastic increase in cropland in the central U.S. over the last 150 years (Figure 1.3) has led to cooler surface air temperatures (Figure 1.4) than we would have had otherwise with natural vegetation. The reason for the cooler temperatures was explained by the greater albedo of croplands (when compared to natural vegetation). Studies of the future climate of the central U.S. with regional climate models continue to show this signal with warming rates in the region expected to be suppressed compared the global rate of future warming (Pan et al., 2004, Figure 1.5).

Changes in precipitation patterns may also be heavily tied to land use change. Koster et al. (2003, 2004) have shown that precipitation patterns are deeply tied to soil moisture patterns,
Figure 1.3  Human modification of land cover in the central and eastern U.S., from Bonan (2001).
Figure 1.4 Impact of human modification of land cover on average daily surface air temperatures, from *Bonan* (1999).
especially over agricultural regions (Figures 1.6, 1.7, 1.8). Croplands, especially in the central U.S., are often modified with tile drainage and/or irrigation (depending on if the crop needs less or more water, respectively, than is provided through precipitation), thus we have another example of how humans may be modifying climate through land use change.

1.1.2 Agriculture and Water Quality

Crop yields in the United States have increased substantially over the past century. The primary crops grown in the U.S. Corn Belt, maize and soybeans, have seen increased yields of approximately 800% and 400%, respectively (Figure 1.9). While the increases in crop yield and production have been extremely beneficial by providing food for the rapidly growing world population, it has come with significant effects on environmental quality. The intense management of the landscape to improve crop yields has deteriorated water quality as nutrients from fertilizers (i.e. nitrogen and phosphorus) and sediments from eroded soil have made their way into groundwater and surface water (Donner, 2003; Donner and Kucharik, 2003; Scanlon...
Figure 1.6  Global cropland density in 2000, from Ramankutty et al. (2008).

Figure 1.7  Coupling strength between the land surface and the atmosphere, based on modeled soil moisture-precipitation feedbacks, from Koster et al. (2004).
One of the most obvious environmental consequences of increased nutrient loading of streams is the hypoxic zone in the Gulf of Mexico (i.e. Gulf Hypoxia). Nutrients leach or run off from croplands into local streams, which then empty into the Mississippi River, which transports the nutrient loaded water into the Gulf of Mexico. The nutrients promote a flourish of algae, which consume oxygen as they die and leave behind an oxygen-deprived environment. The lack of oxygen results in the death or displacement of marine animals, including fish and shellfish, which is destructive not only to the local ecosystem, but also to the fishing industry.

One of the strategies state and federal governments have developed to attempt to mitigate greenhouse gas emissions that are causing climate change on the global scale is to mandate the production and use of biofuels in place of petroleum. In the Energy Independence and Security Act of 2007, Congress indeed mandated that 36 billion gallons of fuel be created from renewable biomass sources (including up to 15 billion gallons from maize-derived ethanol) by the year 2022. While there is considerable disagreement in the scientific literature whether biofuels will actually reduce greenhouse gas emissions (Searchinger et al., 2008), one consideration that appears to be undisputed is that increased biofuel production and use will lead to greater sediment and nutrient transport to streams, with the assumption that fertilizer use will increase
Figure 1.9  U.S. average maize and soybean yield from 1910 to 2010, from *USDA–NASS (2010)*.
to support greater yields of traditional crops (Donner and Kucharik, 2008; Robertson et al., 2008).

1.2 Overview of Land-Surface Models

The previous studies point to the importance of agriculture-climate feedbacks and agriculture’s impact on water quality. It is thus important to make sure that croplands are adequately modeled or considered in modeling studies of future climate change in order to get the total sum effect of human activities (land use change, GHG emissions, fertilization, etc.) on weather, water, and climate.

These next sections will describe some common land surface models (LSMs) that are currently used or are similar to models currently used in regional and global climate models in the context of their ability to model croplands. A comparison of models is summarized in Table 1.1.

1.2.1 Noah LSM

The Noah LSM has been mainly developed since the 1990s when it was first coupled to the Eta model, the operational numerical weather prediction model of the National Centers for Environmental Prediction (NCEP) (Chen and Dudhia, 2001; Ek et al., 2003). The name “Noah” comes from the model’s primary development groups: NCEP, Oregon State University (OSU), the United States Air Force, and the National Weather Service Office of Hydrological Development. Noah is now coupled to two atmospheric models that have found use in regional climate and numerical weather prediction studies: the Weather Research and Forecasting (WRF) model (Skamarock et al., 2005) and the Penn State–National Center for Atmospheric Research fifth-generation Mesoscale Model (MM5). Based on a LSM developed by OSU in the 1980s (Mahrt and Pan, 1984), the Noah LSM is designed to generate reasonable surface fluxes and sub-surface storages of energy and moisture with minimal processing time. It is able to accomplish this goal through using lookup tables that define (minimum and maximum) values of vegetation and soil properties important for determining these fluxes (e.g. albedo, roughness
Regarding cropland modeling, the Noah LSM contains five vegetation types related to croplands or combination of croplands and natural vegetation (Table A.1). The number of choices means that it may fit well for doing broad, equilibrium studies of impacts of greater/lesser cropland extent on weather and climate (like Bonan, 1999) when used as part of a coupled land-atmosphere system. However, because vegetation properties are handled through lookup tables and a time-based interpolation (i.e. phenology is not prognostic), Noah is not well suited for looking at impacts of weather and climate on croplands, nor is it appropriate for looking at dynamic feedbacks between crops and climate. The model also lacks any biogeochemistry modeling (i.e. has no nitrogen cycling), so it does not lend itself to water quality studies. Still, Noah is well suited for its designed purpose: quickly providing surface fluxes to an atmospheric model.

1.2.2 Mosaic LSM

The Mosaic LSM was developed at the National Aeronautics and Space Administration (NASA) in the 1990s to provide a LSM that can be easily coupled to a global climate model (GCM) and can account for some subgrid variability in land cover (Koster and Suarez, 1999). The Mosaic LSM provides the sum effect of subgrid variability by splitting any GCM grid cell that contains multiple land cover types (Table A.2) into a “mosaic” of smaller grids points, or “tiles”, each with a single land cover type. Each tile is simulated separately, with most of the physical calculations based on the Simple Biosphere (SiB) model of Sellers et al. (1986). The model then combines fluxes from each tile for output to each grid point in the GCM. Mosaic has been coupled to the NASA Seasonal-to-Interannual Prediction Project (NSIPP) Atmospheric GCM (Bacmeister et al., 2000) as part of the NASA Global Modeling and Assimilation Office’s coupled GCM (CGCMv1).

The Mosaic LSM’s handling of subgrid variability could be of great use for modeling croplands as they do tend to vary greatly in the types of crops grown (e.g. maize and soybean)
over small distances (1–2 km). However, like the Noah LSM, Mosaic focuses on the simulation of fluxes and storages of energy and moisture and uses lookup tables for vegetation properties. Thus, for modeling of croplands, the same criticisms leveled against Noah apply to Mosaic. Additionally, Mosaic does not include any cropland type of land cover, so croplands are modeled with the grassland land cover.

1.2.3 Community Land Model

In the late 1990s, a group of land surface modelers pooled their resources in an attempt to create a model that could simulate carbon cycling and dynamic vegetation and be easily coupled with a GCM. The National Center for Atmospheric Research (NCAR) LSM (Bonan, 1996), the Institute of Atmospheric Physics (IAP94) land model (Dai and Zang, 1997), and the Biosphere-Atmosphere Transfer Scheme (BATS, Dickinson et al., 1993) were combined to create the Community Land Model (CLM, Oleson et al., 2010). As of the fourth version of CLM, the carbon cycling and dynamic vegetation goals have been accomplished through the additions of a carbon-nitrogen model and a dynamic global vegetation model to the CLM code. Some other novel features of CLM include lake modeling, river transport modeling, and urban area modeling. CLM accounts for subgrid variability by partitioning up each grid cell into “land units”, which are further split into snow and soil columns and, in the case of the vegetation land unit, any number (up to 15) of plant functional types (PFTs). The PFTs are similar in concept to the vegetation and land cover types in the Noah and Mosaic LSMS. CLM has been coupled to the Community Atmosphere Model (CAM) via the Community Earth System Model (CESM, Vertenstein et al., 2009).

Cropland modeling is still a weakness in current, released versions of CLM. CLM, by default, only includes one unique type of crop PFT (Table A.3), and like Noah and Mosaic, many vegetation properties are determined through interpolation of lookup table values. However, the inclusion of the carbon-nitrogen and river routing models in the latest version of CLM could mean that it is appropriate to use in studies of water quality. Such study would require one to do rigorous tuning and validation of the parameters of the crop PFT(s) first.
1.2.4 Agro-IBIS

Applying most current crop models, which simulate phenology and other vegetation properties for many different crop types, to studies of regional weather, climate, and water quality is difficult as the design of these crop models has traditionally been limited to simulation of a single plant or field (Jagtap and Jones, 2002). As previously discussed, most land surface models designed for regional studies (e.g. Noah, Mosaic, CLM) assume rather than simulate vegetation properties that can vary greatly year-to-year and grid point-to-grid point in agricultural regions. Many of these properties, such as biomass and leaf area index, are not only important for simulation of fluxes and storages of energy and water at the land surface but also for policy decisions, such as biofuel mandates that will require more biomass to be produced in the future.

The Agro-IBIS model was developed by combining the dynamic vegetation modeling included in crop models with a current land surface model, the Integrated Biosphere Simulator (IBIS, Foley et al., 1996; Kucharik et al., 2000), in order to create a model that could be used for regional studies of croplands (Kucharik and Brye, 2003; Kucharik, 2003). The IBIS model itself was already novel among LSMs in its growing degree day (GDD) approach to phenology (e.g. timing of budburst, senescence) and dependence of vegetation properties (e.g. biomass, leaf area index) on simulated primary production (i.e. photosynthesis). Agro-IBIS built upon this foundation by adding specific crop plant functional types (maize, soybean, and wheat, Table A.4) and crop management and phenology models (Figure 1.10).

While IBIS uses predefined “biomes” consisting of multiple PFTs to account for subgrid variability, Agro-IBIS ignores the biomes when crops are simulated and uses the same crop PFT for every grid cell. This is a drawback as agricultural regions typically have more than one crop type growing across the landscape. Past studies using Agro-IBIS have bypassed this limitation by partitioning the model’s output based on estimations of fractional area covered by each crop type (e.g. Donner and Kucharik, 2008). However, these studies were all done “offline”; Agro-IBIS has not yet been coupled with any atmospheric model. Should Agro-IBIS be coupled with other model(s) in the future, grid point-to-grid point variability must be
Figure 1.10  Schematic diagram of the Agro-IBIS model, from Kucharik (2003).
reestablished so that regions with natural vegetation are not modeled as croplands.

1.3 Research Plan and Hypotheses

Agro-IBIS has the potential to increase our understanding of agriculture-climate interactions and agricultural impacts on water quality in the past, present, and future by coupling it with atmospheric and/or hydrological models. As part of evaluating Agro-IBIS’s potential use within a coupled model system, I have tested the model uncalibrated at the sub-field scale. Agro-IBIS will not be calibrated to ensure that these offline simulations will follow similarly to simulations done in a coupled environment, where parameters cannot be easily adjusted for every individual model grid point in order to best match observations. The sub-field scale was chosen as an extreme test of the model’s ability to produce spatial variability. The data for this validation test will come from a local agricultural field site, referred to as the Iowa Validation Site (IVS), for the year 2009 when the field was planted with maize.

Although there are many ways in which the Agro-IBIS model could be evaluated, due to practical considerations, I will limit my evaluation to spatial variability and rates of change in soil moisture and leaf area index. I am focused on these variables since they are expected to heavily impact predictions of other variables by the model (e.g. latent heat flux). The hypotheses are:

- The predicted spread of soil moisture will be greater than or equal to the observed spread of soil moisture.
- The average predicted rate of soil water accumulation and drainage during and after precipitation events will match the average observed rate.
- The predicted spread of leaf area index will not be greater than or equal to the observed spread of leaf area index.
- The average predicted rate of leaf area index accumulation over the growing season will match the average observed rate.
<table>
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<tr>
<th>Name</th>
<th>Atm Model</th>
<th>Lineage</th>
<th>Subgrid Var</th>
<th>Phenology</th>
<th>C-N Cycling</th>
<th>Crop Types</th>
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<tr>
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<td>NCAR/IAP94/BATS</td>
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<td>Time-based</td>
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<td>IBIS (LSX)</td>
<td>No</td>
<td>GDD-based</td>
<td>Yes</td>
<td>Maize, soybean, wheat</td>
</tr>
</tbody>
</table>

Table 1.1 Summary of land surface models discussed, including the atmospheric model(s) each is associated with, the each model’s predecessor(s), if the model handles subgrid variability, how the model handles phenology, if the model handles carbon and nitrogen cycling, and which crop types the model simulates.
Differences in the observed soil texture across the IVS should provide the most variable input to Agro-IBIS, so properties relating to soil ought to vary the most in the output. Since Agro-IBIS will also be driven with the range of precipitation values observed at six points across the IVS, we expect that it should be able to reproduce the rates of change and spatial variability observed for soil moisture content.

As Kucharik (2003) found crop yields in Agro-IBIS were insensitive to differences in soil texture, and as many other soil properties (e.g. bulk density) not considered to vary in Agro-IBIS can both vary widely and dominate crop growth at the sub-field scale, we expect that the model will not be able to produce the spatial variability seen in vegetation properties, such as leaf area index. However, I still expect the average rates of growth in both the model and observations to be similar since many processes that dominate growth at the field scale (e.g. accumulation of growing degree days) are well represented in Agro-IBIS.
CHAPTER 2. DATA SOURCES

The majority of the data for this study was collected in 2009 at a 175 ac (approximately 1 km$^2$) field site planted with maize and located to the southwest of Ames, Iowa (Figure 2.1). The site is owned by the Iowa State Foundation and has been managed with traditional tillage and a maize-soybean rotation (odd-even years). The network of data collected at the site attempts to follow the remote sensing observatory outlined in Krajewski et al. (2006). The site has become commonly known as the “Iowa Validation Site” (IVS) as it has been developed to assist in validation of remotely sensed measurements of soil moisture, particularly for the Soil Moisture and Ocean Salinity (Kerr et al., 2010) and Soil Moisture Active/Passive (Entekhabi et al., 2010) missions. As the observations collected at the IVS can provide all of the necessary input for most land surface models (LSMs), it is additionally ideal for validating LSMs, though no such LSM validations have been performed previously at the IVS. This validation study of Agro-IBIS is thus not only novel as the first validation of Agro-IBIS using multiple points at the sub-field scale, but also as one of the first model validations done using data from the IVS.

The IVS is able to provide all of the forcing data that Agro-IBIS requires: above canopy air temperature, above canopy humidity, above canopy wind speed, precipitation, solar radiation, and soil texture (Figure 2.2). Agro-IBIS can optionally be provided the choice of hybrid and planting date, which is known for the IVS. The IVS also provides a wide range of other automated data that can be used to validate the predictions of Agro-IBIS: in-canopy air temperature, in-canopy relative humidity, soil moisture, net radiation (partitioned into its individual components), sensible heat flux, and latent heat flux. To validate Agro-IBIS’s predictions of vegetation properties, manual measurements of biomass and leaf area index were taken. The details of the instruments and methods used to collect these data, along with some
Figure 2.1  Location and shape of the Iowa Validation Site with respect to Agronomy Hall, Iowa State University, Ames, Iowa. The northwest corner of the site is located at \(41^\circ 59.2' \, N, \, 93^\circ 41.4' \, W\).
of the problems encountered with the data, are discussed.

![Figure 2.2 Location of data at the Iowa Validation Site. Letters denote P: precipitation; S: soil texture and automated soil moisture; M: air temperature, relative humidity, and wind speed; R: net radiation; F: eddy covariance.]

2.1 Atmospheric Data

2.1.1 Temperature and Relative Humidity

Temperature and relative humidity measurements were collected at four locations. Above canopy measurements were taken using Campbell Scientific HMP45C temperature and relative humidity sensors. Properly calibrated, the HMP45C has accuracies (for temperatures seen at the IVS) of ±0.3°C for temperature and ±1% for relative humidity. It should be noted that the measurement height was greater than the standard 2 m since the canopy height was expected to (and did) exceed 2 m.
In-canopy measurements were taken using Campbell Scientific HMP50 temperature and relative humidity sensors. Properly calibrated, the HMP50 has accuracies of \( \pm 0.5^\circ C \) for temperature and \( \pm 3\% \) (for 0–90\%) or \( \pm 5\% \) (for 90%–98\%) for relative humidity. The measurement height was adjusted throughout the season to be at half canopy height.

The main problem encountered with the temperature and humidity sensors was a wet bias in one of the HMP45C’s relative humidity readings. Some values of this “bad” sensor were often over 100\%, while the other sensors in the field reported in the upper 90\%’s. We were able to isolate the problem to the sensor, as opposed to user error with e.g. the programming of the data logger, by running a quick test overnight in a lab and finding a “wet bump” in the resulting data (see Figure A.1) when compared to data from a second HMP45C and data from six HMP50s.

Since losing the data from the bad sensor would result in the loss of 25\% of potential model-forcing humidity data, I decided to try to correct the bias so that the data could still be used in Agro-IBIS. I computed an average bias for the data set as the difference between the bad sensor and the average of the other sensors, then subtracted this bias. I also enforced a ceiling of 100\% relative humidity.

2.1.2 Wind

Wind speed was collected at four locations. Two of the locations were also used for eddy covariance measurements and thus used sonic anemometers, the Campbell Scientific CSAT3, to also obtain the three dimensional wind direction. The CSAT3 has a horizontal wind speed accuracy between \( \pm 2\%–6\% \), depending on the direction of the overall wind vector.

The other two locations used cup anemometers, the Campbell Scientific 014A. The 014A has an accuracy of \( \pm 1.5\% \) and a starting threshold of 0.45 m s\(^{-1}\).

There were no major problems with the wind data. While variability was often observed in the data between sites, there were no patterns to suggest that data collected at any particular site was significantly biased.
2.1.3 Precipitation

Precipitation was collected at seven locations. The measurements were taken using dual-tipping rain gauge platforms developed and installed by IIHR-Hydroscience & Engineering laboratory at the University of Iowa in Iowa City, Iowa. The tip size (precision) for the buckets is 0.254 mm. The uncertainty is given with each measurement, following Ciach (2003), and measurements are flagged when differences between the tipping buckets are greater than the uncertainty.

While these rain gauges were developed to essentially quality control themselves, one oddity was identified with one of the stations. The station accumulated 267 mm (29.2%) more precipitation at the end of the year than the average of the other gauges (see Figure A.2). While erroneous accumulations in late-September were the cause of the discrepancy, it was not obvious how to adjust the data since the errors occurred at various times and with various magnitudes and since precipitation data ought to vary somewhat over the field. I decided that six stations with reliable data would probably provide enough variability as input to Agro-IBIS (especially given that for other meteorological forcings, only four points would be provided) and ignored the data from the bad gauge.

2.1.4 Radiation

Radiation was collected at four locations. The measurements were taken using Kipp & Zonen CNR1 net radiometers (sold by Campbell Scientific). The pyranometer measures radiation over a range of 0.305 to 2.8 $\mu$m, while the pyrgeometer measures over a range of 5 to 50 $\mu$m. The accuracy of daily totals is $\pm$10%.

The radiation data required a bit of quality control as values for incoming and reflected solar radiation were often non-zero in the nighttime hours.

2.1.5 Carbon Dioxide and Water Vapor

Carbon dioxide and water vapor concentrations were measured at the two eddy covariance locations. The measurements were taken using LI-COR 7500 open path analyzers.
These data were not quality controlled when they were provided, so bad data was prevalent as one would expect with an eddy covariance system. I did a quick quality control by removing data that led to extremely large/small/unlikely values of carbon dioxide, latent heat, or sensible heat fluxes. I also determined when rainfall was occurring, and removed most of the data during rain events, since it is well known that precipitation affects open path analyzers.

2.2 Soil Data

2.2.1 Soil Texture

Soil clay and sand fractions were measured at 15 locations from 0.1 to 2.1 m using intervals of approximately 20 cm. The resulting textures, computed from USDA’s texture classification system (USDA–NCRS, 2010), are summarized in Table A.5, though note that the depth of some of the measurements were either rounded to the nearest regular interval or spanned across two intervals. For example, a texture measurement made at a depth of 1.73 m is filed under the 1.7 m column. Similarly, a texture measurement made at 1.6 m would be filed under both 1.5 and 1.7 m, assuming no other measurements were made at those depths.

The only other issue with the soil texture data was gap-filling so that the data could be used as input for Agro-IBIS. For missing texture data between layers, I averaged the sand and clay fractions of the nearest layers and computed a texture from the averages. For missing texture data at the bottom of the profile, I copied the deepest known texture in that profile. This is probably a bad assumption from a soil science aspect since it is known that these deep depths were simply ignored in the measurements due to them being glacial till (Logsdon, 2009a, personal communication), and thus difficult to sample. However, from a modeling aspect, I decided that the model results would probably not be significantly affected by this assumption since (in Agro-IBIS) the soil moisture at such depths will not change significantly over a year’s time.
2.2.2 Soil Moisture

Automated soil moisture measurements were taken at nine locations and at five depths: 1.5 cm, 4.5 cm, 15 cm, 30 cm, and 60 cm. The locations were specifically chosen as part of the satellite validation project to characterize the variability in soil moisture across the field. The measurements were taken using Campbell Scientific CS616 water content reflectometers. The CS616 normally has a precision of 0.05% (volumetric water content) and an accuracy of ±2.5%.

The CS616 requires detailed calibration data, including soil temperature data. The soil temperature dependence is critical such that data up to June 12 had to be discarded as the soil temperature data was being recorded incorrectly up to that point. The calibration method itself follows the methods outlined in Logsdon (2009b), which should have improved the accuracy of the soil moisture data to less than ±2.5%.

2.3 Crop Data

2.3.1 Leaf Area Index

Leaf area index (LAI) measurements were made on about a weekly basis at the four locations corresponding to the meteorological (temperature, relative humidity and wind speed) stations. Measurements were made with a LI-COR LAI-2000 plant canopy analyzer. The LAI-2000 measures LAI indirectly by using an optical sensor that observes radiation in a band from 320 nm to 490 nm (ultraviolet A to blue light) above and below a canopy. An algorithm then (assuming a black, azimuthally randomly distributed, and randomly oriented leaf canopy) takes the difference between the above and below canopy measurements and translates it to a LAI. This was ideal since it was a non-destructive method and multiple measurements could be taken quickly.

To characterize the LAI in each of four 30 m × 30 m areas (coinciding with the temperature, relative humidity, and wind speed collecting meteorology stations), we took measurements at three locations in each site. The same three locations were used for each measurement so
that changes in the observed LAI time series were only due to changes in the LAI of each location in each area rather than any spatial variability in LAI that might be present in each area. The number of measurements at each site (3) was chosen to allow the person taking the measurements enough time to visit each site under the similar, ideal sky conditions.

A difficulty with using a sensor like the LAI-2000 is that direct solar radiation can lead to under-estimation of the LAI as the diffraction of light around leaf and stem edges is greater, which causes the sensor to “see” more radiation. This consideration is especially problematic in midday, when the sun is almost directly overhead. The optical sensor also needs to have some minimal amount of light in order to operate correctly. Thus, the ideal operating conditions for using the LAI-2000 (and similar sensors) is during an overcast day where there is essentially no direct radiation but plenty of diffuse radiation.

In 2009, there were not many overcast days. The fallback method was taking measurements around dawn, when the sun could be easily blocked by a cap on the lens of the optical sensor. However, determining out the exact time when the sun is low enough to be blocked and high enough to provide light took a bit of trial and error. Unfortunately, most measurements were taken far too early in the day. Thus, only a small fraction of the LAI measurements taken during the course of the growing season had values reasonable enough to include in this validation.

2.3.2 Biomass

Biomass measurements were also taken near the four meteorological stations. The measurements were originally scheduled to be done twice per month, with measurements in each month done a week apart. The justification for this schedule was that I originally wanted to validate Agro-IBIS on a weekly timescale, though the focus of the validation has since shifted to the ability of the model to reproduce the variability seen at the field.

The measurement procedure involved removing 10 random plants in 30 m × 30 m sites near each of the meteorological stations identified at the beginning of the growing season. The plants were then chopped in order to fit in paper bags, massed wet (with a precision of 0.1 g),
dried for approximately a week at 60°C, then massed dry.

2.3.3 Hybrid, Planting Date, and Yield

The maize hybrids chosen for the IVS in 2009 were 106-day Curry 626-69 HXLLRR2 and 112-day Pioneer 33M14. Averaged, the growing degree days (GDDs) needed for maturity for these two hybrids is approximately 1460 GDD (in °C). The IVS was planted with these hybrids on May 4, 2009.

Total yield was estimated by the University Land Manager to be 35,500 bu with the grain at 20% humidity at harvest, about 192 bu ac⁻¹ when reduced to 15.5% humidity. The land manager also provided a yield map (Figure A.3), though he had less confidence in the absolute numbers reported on it.

2.4 Other Data

Atmospheric data from the Iowa Ag Climate Network located at the Iowa State University Research Farm in Ames, the Automated Surface Observing System (ASOS) station located at the Ames Municipal Airport, and the Automated Weather Observing System (AWOS) station located at the Boone Municipal Airport was combined to fill gaps in the atmospheric forcing data in the periods during 2009 that instruments were not at the IVS (i.e. before planting and after harvest). They were also used to create forcing files from 1989 to 2008, used to spin-up Agro-IBIS. Data for all of these networks were obtained through the Iowa Environmental Mesonet (Herzmann, 2010).
CHAPTER 3. METHODS

3.1 Development of Input for Agro-IBIS

Given the relatively high resolution of data at the Iowa Validation Site (four meteorological stations, six precipitation stations, and 15 soil texture measurements within 1 km²), the original plan in creating the forcing data for Agro-IBIS was to interpolate the data to a 30 m × 30 m grid. However, as will be discussed, this interpolation method could not be used when it was determined that the soil texture measurements were not sufficient enough for a sound interpolation. Thus, the validation study fell back to using an ensemble method, where Agro-IBIS was executed multiple times with different combinations of meteorological and soil data.

3.1.1 Interpolation Method

Amongst all of the forcing data, the difference in soil texture across the IVS ought to drive most of the variability predicted by Agro-IBIS as the texture determines a large number of parameters the model uses (e.g. field capacity, wilting point, saturated hydraulic conductivity) and as the meteorological forcing data is much more homogeneous across the field. Thus, to be able to simulate the sub-field variability within a model domain that corresponds directly to the IVS, the soil texture data needed to be interpolated to a fine grid. Since continuously characterizing crop growth over large areas of the IVS (e.g. 100 m × 100 m) would require an unreasonable amount of field work, we settled on running Agro-IBIS on a grid size of roughly 30 m × 30 m: 0.0004° × 0.0004°. Soil texture data then would have to be interpolated to the same grid space.

Many methods are available to interpolate spatial data. ArcGIS, a mainstream geographic information systems (GIS) application, offers three methods for interpolating data: Inverse
distance weighting (IDW), spline, and kriging. IDW interpolates values at each point by doing a weighted average of nearby points with known values, where the weighting depends on some inverse distance relationship (e.g. inverse square of the distance). Spline interpolation computes values by fitting polynomials (of some degree defined by the user) to the values observed between each pair of points with known values, then using these fitted curves to predict the data for points without known values. Kriging uses information about how the variability of points with known values depends on distance between points (a semivariogram) to determine the most likely value for each point without known values. Amongst these techniques, kriging is often cited as the most scientific as it has a rigorous foundation in statistics.

To interpolate the soil texture, the sand fraction and clay fraction data must be interpolated separately since texture classification is not continuous. The IDW method was attempted first since it is relatively easy to understand and because it is taught in most basic GIS courses. The results (Figure 3.1) were questionable as one would expect the variability to partially match up with the variation in elevation (Figure 3.2) due to how soil particle size fractions are affected differently by erosion. Instead, for a whole variety of tested parameters (number of points used, radius of influence, power), the points with known extreme values of sand and clay content simply stood out as single extreme points, while the rest of the field was predicted to have roughly the same average values.

The spline method, which used a tension spline variation, gave somewhat improved results over the IDW method. The northwest and southern parts of the IVS have sand and clay fractions that match up better with the elevation contours, however it still did not capture the high area in the western part of the IVS, and definitely did not capture the low area in the northeast part of the IVS.

As neither the IDW nor spline interpolation methods fit expectations, the next step was to try the kriging method. Going step-by-step through ArcGIS’s kriging wizard, one could determine before even attempting an interpolation that the result would be meaningless. The computed semivariogram (Figure 3.3) looked like nothing more than a plot of random data. In
Figure 3.1 Attempted interpolation of soil sand and clay fractions using the inverse distance weighting (IDW) and (tension) spline (TS) interpolation methods. Locations of actual texture measurements are shown by the blue diamonds.

Figure 3.2 Elevation map of the Iowa Validation Site. Elevation data from the Iowa LiDAR Mapping Project (ILC, 2009).
order for kriging to work properly, the measured data must have some kind of spatial pattern such that the semivariogram should have a shape that matches with some kind of simple mathematical function (e.g. a logarithmic function) that is near-zero for small distances then increases and levels off at far distances.

In some ways, one could have known that these interpolations would not produce usable results. Given the 7 m variation in elevation at the IVS and that soils tend to form in horizons, the variation in soil texture and other soil properties at depths defined every $x$ m below the surface (as opposed to, e.g., depths defined by elevation above sea level or perhaps by elevation above the rocky C horizon, glacial till in the case of the IVS) should be extremely large. The 0.1 m depth “surface” likely intersects multiple horizons, thus 100 or more times as many texture measurements may be needed to produce a fair interpolation of soil texture at that depth.

### 3.1.2 Ensemble Method

Instead of using interpolated forcing fields to drive Agro-IBIS along a grid, an ensemble method was used to drive the model at a single point with combinations of almost all of the forcing data. The exception was the solar radiation data, which a site-wide average was used since it should vary the least of all the measurements. So, if we name each of the meteorological measurement sites (the sites that measured wind speed, temperature, and relative humidity)
“met1, met2, met3, met4”, each of the precipitation measurement sites “pre1, pre2, ..., pre6”, and each of the soil texture measurement sites “soi1, soi2, ... soi15”, the model was forced with:

\[
\begin{align*}
&\text{met1 + pre1 + soi1} \\
&\text{met1 + pre1 + soi2} \\
&... \\
&\text{met1 + pre1 + soi15} \\
&\text{met1 + pre2 + soi1} \\
&... \\
&\text{met1 + pre6 + soi15} \\
&\text{met2 + pre1 + soi1} \\
&... \\
&\text{met4 + pre6 + soil15}
\end{align*}
\]

The number of combinations of input data meant that Agro-IBIS had to be executed 360 times (and each output file generated 360 times).

### 3.2 Modification of Agro-IBIS

The code for Agro-IBIS as provided was not set up to be run with data from the Iowa Validation Site. A number of modifications had to be made:

1. Modify to use hourly input data collected at the IVS
2. Modify to generate hourly output of variables of interest
3. Modify the number of and depths of soil layers
4. Modify the cultivar selection code

5. Modify the planting date selection code

Modifying the code to use input files generated from IVS data was the most difficult and time-consuming task. As provided, Agro-IBIS was meant to run using climate data sets, e.g. reanalysis done by the National Centers for Environmental Prediction (NCEP) and National Center for Atmospheric Research (NCAR), which drive a weather generator to generate the ambient conditions at each timestep (defined by the user). There was existing code for handling (sub)hourly input, but it was designed for very specific input files (name and format), not very efficient (at the beginning of every year, all input data was read and stored in large arrays), and not well documented. Instead of modifying the existing code, a new module was created to handle all aspects of using hourly data: Opening hourly data files, reading hourly data files, converting hourly data into the correct units, determining other needed variables (e.g. direct and diffuse solar radiation), and storing the data in the correct variables to be read by the other parts of the model. While it took some searching around to find all the right variables where hourly forcing data is stored, the main difficulty was understanding how the other needed variables were generated. Two subroutines, `diurnalmet` and `dailymet`, held the necessary information, though again, it was difficult to decipher due to lack of documentation. Once including the necessary parts of those subroutines (they were renamed to `hourlyMetCalc` and `dailyMetCalc`, respectively) and making sure that they were called at the correct time, the new module for handling hourly input was complete.

Next, the number of soil layers needed to be changed in the model. Beforehand, I decided to modify the input soil texture files to copy the texture at 0.1 m to 0.05 m and do a linear interpolation between 0.1 m and 0.3 m to get a texture for 0.2 m. Then the `hsoi` (soil layer thickness) and `nsoilay` (number of soil layers) variables were updated to match the input files.

Agro-IBIS includes a parameter file (`params.crp`) that allows one to change the properties of the cultivar. However, a slight bug exists in the cultivar choosing code that executes each year. If one does a model simulation for a single year using hourly data, the model, with its standard code, will always choose a hybrid with a GDD-to-maturity rating of 950 GDD (°C)
because of the following logic:

\[
gddmaturity(i,13) = \max(950., \min(\text{gddcorn}(iyear-1), \text{hybgdd}(pft)))
\]

Specifically, in the first year of the simulation, Agro-IBIS chooses the hybrid based on the smaller of GDD defined by the previous year’s GDDs (\text{gddcorn}(iyear-1)) or the hybrid defined by the user (\text{hybgdd}), unless either of those are smaller than 950, in which case 950 GDD is chosen. When doing a single year run, \text{gddcorn}(iyear-1) is 0, so the logic will always default to 950 GDD. As a reference, hybrids planted in the U.S. Midwest typically need around 1500 GDD (°C) to reach maturity. The result of the faulty logic, then, was that most of my first simulations with Agro-IBIS had the crop harvested in late-July.

The final modification added to Agro-IBIS for this validation study was an output module that wrote variables at the end of each hour to plain text files. This method of output made much more sense than dealing with NetCDF (Agro-IBIS’s standard output file type) files since data is only needed for a single point and because otherwise new code for outputting hourly NetCDF files would be needed. Agro-IBIS’s original input/output module only allowed output at daily, monthly, and/or yearly timesteps.

3.3 Execution of Agro-IBIS

Before Agro-IBIS can be used effectively to predict vegetation properties, the model must be spun up since no soil carbon is assumed in a cold start. For my validation study, Agro-IBIS was spun up over 250 years using natural vegetation and with a spin up procedure (\text{soilcspin}) enabled in the model settings. An additional “spin down” was done using maize-soybean rotation for 50 years prior to the validation study. This spin down was done to attempt to set the carbon pool near an equilibrium state for soil under cropping systems.

Getting Agro-IBIS to cycle through the 360 input files required the application of some shell scripting. I wrote a script that cycled to the next set of hourly meteorology files and/or soil texture files, reset the \text{yearsrun.dat} file back to 2008 (otherwise the model would attempt to simulate 2010, then 2011, etc.), replaced the restart files with those that resulted from the
spin up/spin down sequence, and, when each model run was finished, copied the output to a unique directory with a name that documented which input files were used.
CHAPTER 4. RESULTS

Daily means and standard deviations (σ), monthly diurnal means and variances, and hourly means and ranges (where appropriate) were computed for each predicted and observed variable of interest: soil moisture, leaf area index (LAI), in-canopy temperature and relative humidity, surface energy budget components, and biomass. The predicted variables not directly related to my hypotheses (in-canopy temperature, biomass, etc.) were evaluated with regard to how they were affected by the soil moisture and leaf area index predictions. Before these results are discussed, one must first note that any biases in the predicted values will likely be due to the lack of calibration. The version of Agro-IBIS used for this study has been previously tuned to run over large areas (0.5° × 0.5° grid cells) using data sets of climate to drive a weather generator within the model.

4.1 Soil Moisture

Time series of hourly values (Figures 4.1 & 4.2) and daily mean values (Figures 4.3 & 4.4) indicate that Agro-IBIS is able to capture the variability in soil moisture at multiple depths across the field. If one is to disregard the questionable observations at 15 cm and 60 cm starting around August 15 (day 227), the range of predicted values is nearly always greater than the range of observed values.

The ability of Agro-IBIS to generate such large ranges of values is somewhat surprising since the hydraulic properties of the soil (e.g. saturated hydraulic conductivity, porosity) at each depth in each simulation are single values tied to the texture provided at each depth. This is in stark contrast to “real” soils which can exhibit a wide range of these properties for any given texture. Moreover, the IVS is known to have locations of extremely dry or moist
soils due to local elevation maxima or minima. For example, one of the locations at the IVS often experienced prolonged periods of ponded water after heavy rain events. Agro-IBIS does not consider elevation, slope, etc., so, again, it is remarkable that it was able to capture the variability.

The rates of change in the soil water content during and after rainfall events seem to be more pronounced (steeper) than observed in Agro-IBIS at 5 cm, and less pronounced at the lower depths observed. The reason for this model behavior may be due to the failure to calibrate the model. For example, one parameter, the permeability of the lower boundary ($b_{perm}$), could be tuned to match most of the observed behavior. It would likely need to be set lower (more impermeable) so that drainage proceeds more slowly. However, a more permanent, physically appealing solution would be to add a groundwater (i.e. water table) model to Agro-IBIS since the water table’s effect on the vertical water content gradient is likely driving the more sensitive behavior of the soil observed at lower depths.

Looking briefly at the biases in soil moisture, Agro-IBIS’s predictions were drier than observed for the IVS (Figure 4.5). A bias of some sort should be expected at this scale, though, since variation in non-texture soil properties can be large over a single field. Also, the dependence on the bias with depth suggests that tuning the $b_{perm}$ parameter or adding a groundwater model may remove some of this bias.

### 4.2 Leaf Area Index

As the rate of accumulation was nearly the same in both the model and observations, Agro-IBIS’s predictions of leaf area index suggest that emergence happened four to five days too early in the model (Figure 4.6). While the hybrid and planting date were fixed in the model according to what happened at the IVS, this result is likely an issue of calibration. Some direct examples would be the failure to tune the leaf area expansion and phenology control parameters, such as maximum LAI, the fraction of GDD-to-maturity needed for emergence, and the LAI curve equation coefficient. Even if these parameters were set correctly for the IVS, there could still be a bias in emergence due to the aforementioned bias in soil moisture.
Figure 4.1 Example 20-day time series for hourly predicted and observed soil moisture at 5 and 15 cm depths from June 29 to July 19. Solid lines are mean values; highlighted regions represent the range of values.
Figure 4.2  Example 20-day time series for hourly predicted (sim) and observed (obs) soil moisture at 30 and 60 cm depths from June 29 to July 19. Solid lines are mean values; highlighted regions represent the range of values.
Figure 4.3  Time series for predicted (sim) and observed (obs) daily average soil moisture at 5 and 15 cm depths. Solid lines are mean values; highlighted regions are ±2σ.
Figure 4.4  Time series for predicted (sim) and observed (obs) daily average soil moisture at 30 and 60 cm depths. Solid lines are mean values; highlighted regions are ±2σ.
Figure 4.5 Diurnal averages show that the biases in soil moisture range from -0.07 m$^3$ m$^{-3}$ at 5 cm depth to -0.13 m$^3$ m$^{-3}$ at 60 cm depth.
or other biases in the model. For instance, a drier soil may have led the model to over-predict soil and air temperatures and thus accumulate GDDs faster than observed. Regardless of the cause, the bias in LAI was unfortunate as it seemed to affect the model’s prediction of other variables, such as in-canopy temperature, which will be discussed later.

For the period which observed LAI data is available, the rate of accumulation was similar in both observations and in Agro-IBIS. The rates are particularly close if one discounts the LAI data taken close after a storm on July 10 (day 191, see Figure 4.7): 0.17 m² m⁻² day⁻¹ predicted versus 0.06–0.15 m² m⁻² day⁻¹ observed. As the stunted growth of the maize at one of the locations kept one series of values increasingly well below average, the higher range of the observed rates is likely closer to the field average rate.

The July 10 storm and the area of stunted growth also combined to widen the range of LAI values observed at the IVS. While Agro-IBIS predicted a fairly wide range of LAI values (up to 0.5 m² m⁻²), the variability in observed LAI was typically far greater, sometimes with a range of over 1 m² m⁻². As Agro-IBIS has no means of simulating the impacts or locations of compacted soils (which was thought to cause the stunted growth), this was to be expected. However, speaking from personal experience at the IVS, if one were to have taken more LAI measurements at each location and perhaps conglomerate them across larger areas than 30 m × 30 m, the range observed would likely be much closer to that predicted by Agro-IBIS.

4.3 Biomass

Because of the difficulties involved in scaling biomass measurements taken in small areas at the IVS to the kilogram of carbon per square meter basis used in Agro-IBIS, the observed and predicted values were scaled using the maximum value in each data set (Figure 4.8). Initially, it appears that Agro-IBIS has a lag in its accumulation of biomass compared to observation, which is opposite of what was seen in the leaf area index comparison. However, the observations are a bit suspect considering they suggest that biomass accumulations stopped in mid-August. Maturity for maize in Iowa is usually reached between mid-September and early October.
Figure 4.6  Full time series and zoomed (June 20 to July 20) time series of leaf area index measurements (obs) and predictions (sim). The highlighted region represents the range of values predicted or observed.
Figure 4.7  A bow echo with severe winds passed over the Iowa Validation Site on the morning of July 10, 2009. Archived NEXRAD image obtained from the Iowa Environmental Mesonet (Herzmann, 2010)
Moreover, 2009 was a cooler year than average, so maturity may have been even later than observed (in these biomass measurements) or predicted.

Figure 4.8 Time series of scaled average biomass measurements/predictions. The scaling was done by dividing by the maximum value of biomass measured/predicted.

It is difficult to pinpoint any potential problems with Agro-IBIS's simulation of biomass due to the lack of trust in the observations. With the early emergence seen in the LAI data, one would expect to see a positive bias in the biomass, at least until grainfill, but it is impossible to assert that is indeed the case with the data at hand.

4.4 Surface Energy Budget

4.4.1 Net Radiation

The diurnal values of the components of the radiation budget predicted by Agro-IBIS are often within the range of values observed at the IVS or otherwise shifted by an hour or less (Figure 4.9). These results seem to be reasonable, however one problem is that the incoming
solar radiation values should be the same in the model as was observed as the model was forced with the observed values. The reason for the discrepancy may be tied to the method Agro-IBIS uses to partition the incoming solar radiation into direct radiation and diffuse radiation or otherwise some computing error when creating the input data set.

![Surface Radiation Budget - Diurnal Averages (August)](image)

Figure 4.9  Diurnal patterns in the different radiation budget components ($R_n$ – net radiation; $S_{in}$ – incoming solar; $S_{refl}$ – reflected solar; and $I_{net}$ – net infrared), predicted (sim) and observed (obs) during August. Highlighted regions are ±2σ. Note that the signs of the solar components have been made to be positive for this graph.

The error in the incoming solar radiation did seem to drive a negative bias in net radiation (Figure 4.10), though a slight positive bias in albedo (Figure 4.11) was also to blame. As will be discussed, the model seemed less sensitive to this negative bias in net radiation compared to the bias in leaf area index.
Figure 4.10  Biases in the diurnal mean surface radiation budget. Positive values indicate over-prediction by Agro-IBIS.

Figure 4.11  Bias in the diurnal mean albedo ($S_{refl}/S_{in}$). Positive values indicate over-prediction by Agro-IBIS.
4.4.2 Sensible and Latent Heat Flux

The diurnal patterns in the surface energy components (here limited to net radiation, sensible heat flux, and latent heat flux) also matched well with the observed patterns (Figure 4.12). The main discrepancy was a two-hour shift in the timing of peak sensible and latent heat fluxes, with Agro-IBIS having predicted the peaks later.

As one would expect, the net radiation bias forced biases in the other surface energy components (Figure 4.13). This was most obvious in the latent heat flux bias, which essentially tracked the net radiation bias throughout the day. The sensible heat flux bias was puzzling, and I believe it is a result of the leaf area index bias keeping the canopy warmer than it should have been otherwise, as will be discussed in the next section. Overall, the warm sensible heat flux bias and dry latent heat flux bias led to a significant bias in the Bowen ratio (the ratio of sensible heat to latent heat), ranging from 0.1 to 0.6 during the day (Figure 4.14).

4.5 In-canopy Temperature and Humidity

The time series and diurnal patterns in in-canopy temperature and relative humidity (Figures 4.15 & 4.17 & 4.16), suggest that Agro-IBIS was also able to capture the spread observed in these variables as well. A curiosity, though, is the warm bias, which existed despite a negative net radiation bias in the model. The explanation for this bias reached back to the over-accumulation of leaf area in the model. By over-predicting leaf area index, Agro-IBIS should have had a positive bias in the conductance between the canopy air space and the air above. This allowed the canopy air space to heat up more during the day as the influence of the cooler air above was diminished.

Because of the warm bias, the bias in the relative humidity is deceiving as a temperature bias affects the vapor saturation point. Indeed, computing dew point temperatures shows that Agro-IBIS had a slight wet bias as the bias in the diurnally averaged dew point temperature ranged from 1–2°C throughout the day.

Overall, the model gave reasonable predictions of in-canopy temperature and relative humidity, considering the major biases likely stemmed from a failure to calibrate the leaf area
Figure 4.12  Diurnal patterns in the different surface energy budget components ($R_n$ – net radiation; $H$ – sensible heat flux; $\lambda E$ – latent heat flux) predicted (sim) and observed (obs) during August. Highlighted regions are ±2σ. Note that the signs of the components have been made to be positive during the day for this graph.
Figure 4.13 Biases in the diurnal mean surface energy budget. Positive values indicate over-prediction by Agro-IBIS.
Figure 4.14  Bias in the Bowen ratio ($\beta$). Positive values indicate over-prediction by Agro-IBIS.
Figure 4.15  Diurnal patterns of in-canopy temperature and in-canopy relative humidity during the month of August as predicted (sim) and observed (obs).
Figure 4.16 Example time series of hourly values of in-canopy temperature and in-canopy relative humidity as predicted (sim) and observed (obs) for August 18-25.
Figure 4.17 Time series of the daily average values of in-canopy temperature and in-canopy relative humidity as predicted (sim) and observed (obs).
index parameters. The peaks in predicted temperature and relative humidity nearly always matched the timing of the peaks in the observations, which was somewhat unexpected given the lag in the peaks of the surface energy budget components.
CHAPTER 5. CONCLUSIONS

Agro-IBIS is among the first process-based models that has successfully simulated crop growth and some aspects of management over large spatial scales. However, using Agro-IBIS at fine scales, such as over a field the size of the Iowa Validation Site, requires one to answer a number of questions, for example:

- How do I deal with insufficient soil data to run Agro-IBIS in a grid?
- How do I handle bad data when that data is needed as input to the model?
- How do I scale certain variables (e.g. biomass) from a few points in the field up to the scale that Agro-IBIS uses? Or, oppositely, how do I scale Agro-IBIS’s variables down to the scale of points in the field?

I have learned through facing and answering these questions that both modeling experiments and observational experiments never proceed quite as planned. My project certainly did not end up as planned; I originally wanted to run Agro-IBIS on a fine grid with interpolated soil and meteorological data, expecting to end up with a yield map like Figure A.3. Yet switching gears and looking at variability and diurnal cycles forced me to learn more about a concept I am deeply interested in: *how changes in land cover can have significant impacts on local weather and climate.*

The necessary tasks that were accomplished to facilitate the validation of Agro-IBIS at the Iowa Validation Site included:

- Collecting leaf area index and biomass measurements at four locations at the IVS.
- Creating an ensemble of data sets for driving Agro-IBIS from data collected at the IVS.
• Modifying Agro-IBIS to use this ensemble data set as input and to output variables used in the validation.

• Executing Agro-IBIS and compiling the resulting 360 sets of output files in a digestible format.

The results of the validation study showed that Agro-IBIS can reproduce the variability in many plant, soil, and atmospheric properties within a single field. The importance of calibration when using a model at such a fine scale was highlighted, along with the importance of understanding the limitations of a model. The purposed failure to calibrate Agro-IBIS led to early emergence and accumulation of leaf area index. The LAI bias led to a number of other biases, including a warm bias in the predicted in-canopy temperature and sensible heat flux.

As for the specific hypotheses that were posed:

• The predicted spread of soil moisture was usually greater than or equal to the observed spread.

• The average predicted rate of soil water accumulation and drainage did not match the observed rate; the rates were greater than observed.

• The predicted spread of leaf area index was usually not greater than or equal to the observed spread; however, the observations were questionable due to the small number of observations and the influence of a severe storm on the method of observation.

• The average predicted rate of leaf area accumulation matched closely with the upper end of the spread of rates in the observations; the upper end of the observed spread was expected to match most of the field as a small region of stunted growth defined the lower end of the spread.

As Agro-IBIS was able to capture most of the variability observed at the IVS and as the biases due to calibration would likely disappear if Agro-IBIS were used over more fields, I would deem Agro-IBIS a good candidate for coupling with other models – specifically regional
climate models and data assimilation schemes – in order to predict changes in yield, climate, and water quality over agricultural regions in the future.
CHAPTER 6. RELATED AND FUTURE WORK

6.1 Related Work

I have been tasked with three major responsibilities indirectly related to my work on validating Agro-IBIS at the Iowa Validation Site:

Attending Agro-IBIS Workshops

Twice a year, users of the Agro-IBIS model meet at one of the user’s university to share their work with the model, get feedback on their research ideas, and assist others in their work.

Developing and Maintaining ISU’s Archive of SMOS Data

As I am part of the research group at Iowa State involved with validating measurements from the Soil Moisture and Ocean Salinity (SMOS) mission satellite, I have a vested interest in making sure we are able to help with the mission. In early 2010, we were provided access via FTP to SMOS data for our region of interest. However, the data is quite large, with a week’s worth of data sometimes requiring 1 GB of space (and even more now since we have been allowed access to level 2 data). I was able to make use of my personal knowledge of computers and systems administration to build, program, and maintain an automated storage server for archiving and processing all of the SMOS data available to us. As of 2010-11-12, the server has archived about 56 GB of SMOS data, or 3% of the capacity of the 3 TB RAID 10 disk array installed.

Advocating and Maintaining the Agro-IBIS Code Repository

At the first Agro-IBIS Workshop, I, along with a now former Agro-IBIS user Bill Sacks, proposed a code repository and version system for the Agro-IBIS code. With each user...
adding this and that to the code, it was important to have a central location for code
that we knew worked and had known bugs fixed. While Bill took the initiative to create
the repository, it has now fallen to me. I believe Agro-IBIS is an important model, so I
plan to keep the code repository in top shape, adding features as necessary.

6.2 Future Work

The next task that ought to be done is a validation of Agro-IBIS at the Iowa Validation
Site in 2010, when soybeans were planted. Ames was heavily impacted by flooding in 2010,
and many locations at the IVS were under water for extended periods of time, so it should be
a good test of how well Agro-IBIS can handle extreme weather and climate. As Agro-IBIS is
a one dimensional model and has no runoff routing to pool water in the low-lying areas of its
domain, an obvious hypothesis is that Agro-IBIS will severely under-predict soil moisture and
over-predict leaf area index and yield in the lower parts of the IVS.

One of the obvious applications of Agro-IBIS would be coupling it to an atmospheric
model in order to fully simulate all of the soil-plant-water-atmosphere feedbacks discussed in
the Introduction. The Land Information System modeling framework has already been coupled
with a current atmospheric model, the Weather Research and Forecasting (WRF) model. The
LIS also has a developer’s guide available for people who want to couple other land surface
models to it. Thus, a natural next step would be coupling Agro-IBIS to the LIS, which would
not only improve the LIS’s prediction of land variables in agricultural regions, but also facilitate
a coupling between Agro-IBIS and an atmospheric model (WRF).

Before Agro-IBIS gets coupled to any other model, though, I need to take another thorough
look through the code to determine why the solar radiation output by the model does not match
with the solar radiation input. Accumulating an extra 40 W m$^{-2}$ day$^{-1}$ at the land surface
could cause a cascade of errors in other parts of a coupled system.
APPENDIX

Figures

Figure A.1 A “wet bump” and wet bias towards higher relative humidities was found with one of the HMP45 sensors used at the field. Data shown here was recorded in a lab with adjacent sensors.
Figure A.2 One precipitation gauge recorded significantly more precipitation, with a near-discontinuous jump in late September.
Figure A.3 Yield map at the Iowa Validation Site (known internally at Iowa State University as the Been Field) for 2009 (Burns, 2010, personal communication).
### Tables

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<th>Vegetation Type</th>
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Table A.1  List of default vegetation types in the Noah LSM version 3.2 (*NCAR-RAL*, 2010).
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<tr>
<td>2</td>
<td>Broadleaf Deciduous Trees</td>
</tr>
<tr>
<td>3</td>
<td>Needleleaf Trees</td>
</tr>
<tr>
<td>4</td>
<td>Grassland (Groundcover)</td>
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<tr>
<td>5</td>
<td>Broadleaf Shrubs</td>
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<td>6</td>
<td>Dwarf Trees (Tundra)</td>
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Table A.2 List of surface types in the Mosaic LSM (*Koster and Suarez*, 1999).

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<td>Broadleaf Evergreen Tree – Tropical</td>
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<td>5</td>
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<td>Broadleaf Deciduous Tree – Boreal</td>
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<td>8</td>
<td>Broadleaf Evergreen Shrub – Temperate</td>
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<td>11</td>
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<td>C₃ Grass</td>
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Table A.3 List of plant functional types (PFTs) in the Community Land Model LSM version 4.0 (*Oleson et al.*, 2010). Note that Crop2 is, by default, a copy of Crop1, made available for simple modification.
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<td>4</td>
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<td>Temperate Broadleaf Cold-Deciduous Trees</td>
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Table A.4 List of plant functional types (PFTs) in (Agro-)IBIS.
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<td>713</td>
<td>Sandy Clay Loam</td>
<td>Sandy Clay Loam</td>
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<td>Silty Clay</td>
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</tr>
</tbody>
</table>

Table A.5: Soil textures measured at the Iowa Validation Site. An “undefined” texture denotes where measurements were omitted. Depths are approximate for some measurements (see Section 2.2.1).
Code

hourlymet.f

  c hourlymet.f
  c Created by Jason Patton 2010-03-25
  c
  c Holding place for subprograms dealing with using hourly met data

  ---------------------------
  FUNCTION getUnit(varName)
  ---------------------------
  c Created by Jason Patton 2010-03-24
  c
  c Lets user define units for variables for
  c hourly met data. These units are then
  c retrieved using getUnit function.
  c
  c Elevation is also defined
  c
  c Output var
      CHARACTER*5 getUnit
  c
  c Input var
      CHARACTER*4 varName
  c
  c Processing var
      CHARACTER*5 units(8)

  c Temperature (C, K, or F)
      units(1) = 'F'

  c Humidity
  c    dwpC = Dewpoint C
  c    dwpK = Dewpoint K
  c    dwpF = Dewpoint F
  c    rhpct = RH Percent (0% - 100%)
  c    rhfrc = RH Fraction (0.0 - 1.0)
  c    mixgg = Mixing Ratio (g/g)
  c    mxgkg = Mixing Ratio (g/kg)
      units(2) = 'rhpct'

  c Wind (ms = m/s, kmph = km/h, mph = mi/h, or kts = nm/h)
      units(3) = 'mph'

  c Precip (mm, cm, or in)
units(4) = 'mm'

c Solar Radiation (Wm^2 = W m^-2, kcal = kcal m^-2 h^-1)
   units(5) = 'kcal'

c Pressure (mb, kPa, in)
   units(6) = 'in'

c Elevation in meters
   Still a character, but we convert that later
   units(7) = '309'

c Carbon Dioxide (ppm, mgm3 = mg/m3)
   units(8) = 'ppm'

c Spit back units as function
   IF(varName == 'Temp') getUnit = units(1)
   IF(varName == 'Humi') getUnit = units(2)
   IF(varName == 'Wind') getUnit = units(3)
   IF(varName == 'Prec') getUnit = units(4)
   IF(varName == 'Sola') getUnit = units(5)
   IF(varName == 'Pres') getUnit = units(6)
   IF(varName == 'Elev') getUnit = units(7)
   IF(varName == 'Carb') getUnit = units(8)
   RETURN

-- END FUNCTION getUnit
--

IMPLICIT NONE

INTEGER availYears(21) ! Change these based on years available

SUBROUTINE openHourlyMet (thisYear, seed, doSpinup)

This should run at the beginning of every year

1. Opens hourly data files named by year with UNIT = 13
2. Checks for open errors and stops program if error found

   Force explicitly defined variables
   IMPLICIT NONE

   Constants

cIncoming vars
INTEGER thisYear
INTEGER seed
INTEGER doSpinup

cProcessing vars
LOGICAL isLeap, is_leap
INTEGER i, oer, metYear, randYear
CHARACTER*4 charfile
CHARACTER*4 checkYear

c Set curent year
metYear = thisYear
randYear = 0

c Check for leapyear
isLeap = IS_LEAP(metYear)

c If this is a spinup case, get a random year of data
IF(doSpinup .EQ. 1) THEN
  DO
    CALL RANDOM_CHOICE(randYear, availYears, 21, seed)
  c Loop until we get a match for leap year/not leap year
    IF(
      > (( isLeap) .AND. ( IS_LEAP(randYear)))
      > .OR.
      > ((.NOT. isLeap) .AND. (.NOT. IS_LEAP(randYear)))
      > ) EXIT
  ENDDO
  WRITE(*,*) 'Spinup run, using data from year (', randYear,')'
  ENDIF

c Tell user that they’re using hourly data this year
WRITE(*,*) 'Using hourly data for year (', metYear,')'

c Put year into string for filename
IF(randYear .NE. 0) THEN
  WRITE(charfile,'(I4)') randYear
ELSE
  WRITE(charfile,'(I4)') metYear
ENDIF
c Open file
OPEN (UNIT = 13, FILE = 'input/hourly//'charfile, IOSTAT=oer)

c Check for error
IF (oer .NE. 0) THEN
    WRITE(*,*) 'Error: Hourly data file unopenable for:'
    WRITE(*,*) ', metYear
    STOP
ENDIF

c Check for header, if not there, rewind file
so file pointer is positioned properly
READ(13,*) checkYear
IF(checkYear .EQ. charfile) REWIND(13)

RETURN

c ----------------------------------------------------
END SUBROUTINE openHourlyMet

c ----------------------------------------------------

SUBROUTINE readHourlyMet (thisYear, thisMonth, thisDay,
.   thisStep, thisDOY, irrigate, irrlength, irrstart,
.   irrend)

c ----------------------------------------------------

END SUBROUTINE readHourlyMet

Get needed modules
USE comgrid
USE compar
USE comwork
USE comatm
USE comhyd
USE comsum
USE combcs
USE comcrop
USE comnitr
c Force explicitly defined variables
IMPLICIT NONE

c Incoming vars
INTEGER thisYear, thisMonth, thisDay, thisStep,
   thisDOY, irrigate, irrlength, irrstart, irrend

c Read vars
INTEGER metYear, metMonth, metDay, metHour
REAL metTemp, metHum, metWind, metPrec,
   metSolar, metPres
   , metElev ! Uncomment if reading Elevation
   , metCO2 ! Uncomment if reading CO2

FUNCTION vars
CHARACTER*5 getUnit

FUNCTION vars
INTEGER ier, ! Input status
   i ! General counter
REAL metSH, ! Computed specific humidity
   metVP, ! Computed vapor pressure
   minTemp, ! Computed minimum temp
   maxTemp, ! Computed maximum temp
   sumTemp, ! Sum of all temps for day
   avgTemp, ! Average temp for day
   sumSH, ! Sum of all specific humidity for day
   avgSH, ! Average specific humidity for day
   sumPrec, ! Sum of all precip for day
   sumWind, ! Sum of all wind speeds for day
   avgWind ! Average wind speed for day

c Save summation variables
SAVE sumTemp, sumSH, sumPrec, sumWind

C Include functions for humidity calculations
INCLUDE 'comsat.h'

C <BEGIN Read from file>
C
C Current file structure is:
C Year, Month, Day, Hour, Temp, Hum, Wind, Prec, Solar, Pres

READ(13, *, IOSTAT = ier)
metYear, metMonth, metDay, metHour,
metTemp, metHum, metWind, metPrec,
metSolar, metPres

> , metCO2 ! Uncomment if reading CO2

Check for read error
IF (ier .NE. 0) THEN
  WRITE(*,*) 'Error reading file for:'
  WRITE(*,*) thisYear
  WRITE(*,*) ' at:'
  WRITE(*,*) thisYear, thisMonth, thisDay, thisStep
  STOP
ENDIF

Check for date/time consistency
IF ( (thisMonth .NE. metMonth) .OR.
> (thisDay .NE. metDay) .OR.
> (thisStep .NE. (metHour + 1)) )
> THEN
  WRITE(*,*) 'Date mismatch at:'
  WRITE(*,*) ' IBIS Year', thisYear, 'Data Year', metYear
  WRITE(*,*) ' IBIS Month', thisMonth, 'Data Month', metMonth
  WRITE(*,*) ' IBIS Day', thisDay, 'Data Day', metDay
  WRITE(*,*) ' IBIS Step', thisStep, 'Data Hour', metHour
  STOP
ENDIF

<BEGIN Convert data to IBIS-friendly units>

The current conversion factors are only for Jason Patton's M.S. Thesis
Feel free to add your own, though.

Temperature needs to be in K
IF(getUnit('Temp') == 'F') THEN ! F to K
  metTemp = 273.16 + ((metTemp - 32.0)*(5.0/9.0))
ENDIF

Pressure needs to be in Pa
Though this seems out of order, pressure is needed
for specific humidity calc
IF(getUnit('Pres') == 'in') THEN ! inHg to Pa
  metPres = 3386.39 * metPres
ENDIF
Humidity needs to be converted to specific humidity and vapor pres

\[
\text{IF(getUnit('Humi') == 'rhpct') THEN ! \% to *}
\]

Set RH to 99\% if > 99\%:

\[
\text{IF(metHum .GT. 99.0) metHum = 99.0}
\]

\[
\text{metSH = QSAT((metHum/100.0) * ESAT(metTemp), metPres)}
\]

\[
\text{metVP = (metHum/100.0) * ESAT(metTemp)}
\]

```
ENDIF
```

Precipitation needs to be in mm:

***NOTE*** This assumes that precip data is FOR next hour,
not FROM past hour:

\[
\text{IF(getUnit('Prec') == 'mm') THEN ! mm to mm}
\]

\[
\text{metPrec = metPrec}
\]

```
ENDIF
```

Wind speed needs to be in m s\(^{-1}\) and between 2.5 and 25.0:

\[
\text{IF(getUnit('Wind') == 'mph') THEN ! mph to m s\(^{-1}\)}
\]

\[
\text{metWind = 0.44704 \times metWind}
\]

```
ENDIF
```

\[
\text{metWind = MAX(2.5, MIN(25.0, metWind)) ! 2.5 < ua < 25.0}
\]

Solar radiation needs to be in W m\(^{-2}\):

\[
\text{IF(getUnit('Sola') == 'kcal') THEN ! kcal hr\(^{-1}\) to W}
\]

\[
\text{metSolar = 1.162 \times metSolar}
\]

```
ENDIF
```

```
<c <BEGIN Push to IBIS weather vars>
</c>

CALL CONST(ta, npoi, metTemp)
CALL CONST(rh, npoi, metHum)
CALL CONST(qa, npoi, metSH)
CALL CONST(ua, npoi, metWind)
CALL CONST(precip, npoi, metPrec)
CALL CONST(cloud, npoi, metSolar)
CALL CONST(rads, npoi, metSolar)
CALL CONST(psurf, npoi, metPres)
```

This subroutine will calculate everything we don’t have:

- solar transmission, direct & diffuse
- infrared transmission
- snow/rain rates
- irrigation (if needed)

CALL hourlyMetCalc(thisStep, thisDOY, irrigeate, irrlength, irrstart, irrend)
c
<BEGIN Calculate daily vars (tmax, tmin, tavg)>
c
First hour of day, reset min and max temps and sums
  IF(metHour .EQ. 0) THEN
    CALL CONST(tmin, npoi, metTemp)
    CALL CONST(tmax, npoi, metTemp)
    sumTemp = 0.0
    sumSH = 0.0
    sumPrec = 0.0
    sumWind = 0.0
  ENDIF

c Compare tmin/tmax to current value and set
  minTemp = MIN(tmin(1), metTemp)
  maxTemp = MAX(tmax(1), metTemp)
  CALL CONST(tmin, npoi, minTemp)
  CALL CONST(tmax, npoi, maxTemp)

c Sum up variables
  sumTemp = sumTemp + metTemp
  sumSH = sumSH + metSH
  sumPrec = sumPrec + metPrec
  sumWind = sumWind + metWind

c Last hour of day, compute averages and call dailymet
  IF(metHour .EQ. 23) THEN
    avgTemp = sumTemp/(24.0) ! Average temp from hourly Ts
    avgTemp = (minTemp + maxTemp) / 2.0 ! Average temp from min/max
    avgSH = sumSH/(24.0)
    avgWind = sumWind/(24.0)
    CALL CONST(td, npoi, avgTemp)
    CALL CONST(qd, npoi, avgSH)
    CALL CONST(precip, npoi, sumPrec)
    CALL CONST(ud, npoi, avgWind)
    CALL dailyMetCalc(thisMonth, thisDay, 0)
  ENDIF

RETURN

c ----------------------------------------------------
END SUBROUTINE readHourlyMet

END SUBROUTINE readHourlyMet

c
SUBROUTINE closeHourlyMet()

Created by Jason Patton 2010-03-24

This should run at end of each year

1. Closes currently open hourly data file (UNIT = 13).

Force explicitly defined variables
IMPLICIT NONE

Close file
CLOSE(13)

RETURN

END SUBROUTINE closeHourlyMet

Additional weather functions called by the above subroutines

SUBROUTINE hourlyMetCalc(istep, jday, irrigate, ilens, starti, endi)

uses:

USE comgrid
USE compar
USE comatm
USE comveg
USE comwork
USE comhour
USE comcrop
USE comnitr

IMPLICIT NONE

Arguments

INTEGER istep, ! current time step (between 1 and niter)
jday, ! current day of year
irrigate ! irrigation switch
REAL
> ilens, ! length of irrigation events
> starti, ! start time of irrigation events
> endi, ! end time of irrigation events
> truecloud ! cloudiness computed by atm transmission

INTEGER i, ! loop indice
> jj, ! latitude
> ib ! waveband number 1= visible, 2= near-IR

REAL time, ! time in seconds since midnight
> rtime, ! time in hours
> orbit, ! earth's orbital angle (around the sun), rad
> xdecl, ! solar declination angle
> sw, ! effective solar constant
> xlat, ! latitude in radians
> fdiffuse, ! fraction of diffuse solar radiation
> wfrac, ! fraction of energy in each waveband
> emb,
> ea,
> ec,
> dtair,
> dtcloud

INCLUDE 'comsat.h'

c Externals

REAL get_time ! from utilities.f
REAL calc_orbit, calc_xdecl, calc_sw ! from toa_radiation.f

c * * * calendar and orbital calculations * * *

**Calculate time in hours**

time = get_time(istep)
rtime = time / 3600.0

**Calculate some variables related to top-of-atmosphere radiation**

orbit = calc_orbit(jday)
xdecl = calc_xdecl(orbit)
sw = calc_sw(orbit)
c do for all gridcells
  DO 100 i = 1, npoi
  ----
  c * * * solar transmission & diffuse/direct calculations * * *
  ----
  c calculate the latitude in radians
  jj = latindex(i)
  xlat = latscale(jj) * pi / 180.0
  c fetch the cosine of the solar zenith angle from pre-computed values
  coszen(i) = coszen_pre(jj, istep)
  c find daylength to be used in pheno subroutine
  c WJS 02.03.10: This equation used to be different, but I believe that
  c the old version gave incorrect results at any time step when coszen(i)
  c was > 0. This new version gives the same (correct) daylength in each
  c time step. Thus it should probably be moved outside of 'diurnal' (and
  c outside of the sub-daily loop entirely).
  daylength(i) = (180./pi)*((2.*60.)/15.)*
    > (ACOS(-(SIN(xlat)*SIN(xdecl)) / (COS(xlat)*COS(xdecl))))
  c calculate the solar transmission through the atmosphere using direct
  c measurements
  c transmission is fraction of insolation that makes it to the surface
  trans(i) = rads(i) / sw
  c calculate the fraction of indirect (diffuse) solar radiation
  c based upon the cloud cover
  c note that these relationships typically are measured for either
  c monthly or daily timescales, and may not be exactly appropriate
  c for hourly calculations
  c method i --
we use a simple empirical relationships from Nikolov and Zeller (1992)


\[
\text{fdiffuse} = 1.0045 + 0.0435 \times \text{trans}(i) - 3.5227 \times \text{trans}(i)^2 + 2.6313 \times \text{trans}(i)^3
\]

IF (\text{trans}(i) \gt 0.75) \text{fdiffuse} = 0.166

method ii --

another method was suggested by Spitters et al. (1986) based on long-term data from the Netherlands


if ((\text{trans}(i) \lt 0.07)) then
\text{fdiffuse} = 1.0
else if ((\text{trans}(i) \gt 0.07).and.(\text{trans}(i) \lt 0.35)) then
\text{fdiffuse} = 1.0 - 2.3 \times (\text{trans}(i) - 0.07)^2
else if ((\text{trans}(i) \gt 0.35).and.(\text{trans}(i) \lt 0.75)) then
\text{fdiffuse} = 1.33 - 1.46 \times \text{trans}(i)
else
\text{fdiffuse} = 0.23
endif

do for each waveband

\[
\text{DO 120 ib = 1, nband}
\]
calculate the fraction in each waveband
\[
\text{wfrac} = 0.46 + 0.08 \times \text{FLOAT}(ib - 1)
\]
calculate the direct and indirect solar radiation
\[
\text{solad}(i,ib) = \text{wfrac} \times \text{rads}(i) \times (1. - \text{fdiffuse})
\]
\[
\text{solai}(i,ib) = \text{wfrac} \times \text{rads}(i) \times \text{fdiffuse}
\]
120 CONTINUE
clear-sky emissivity as a function of water vapor pressure
and atmospheric temperature

calculate the ir emissivity of the clear sky

\[
\begin{align*}
emb &= 0.01 \times \left( psurf(i) \times qa(i) / (0.622 + qa(i)) \right) \\
e a &= 0.70 + 5.95 \times 10^{-5} \times emb \times \exp(1500.0 / ta(i)) \\
\end{align*}
\]

c assign the ir emissivity of clouds (assume they are ~black in the ir)

\[
e c = 0.950
\]

c assign the temperature difference of emissions (air + cloud) from
the surface air temperature

\[
\begin{align*}
dtair &= 2.0 \\
dtcloud &= 2.0
\end{align*}
\]

c total downward ir is equal to the sum of:
c (1) clear sky contribution to downward ir radiation flux
c (2) cloud contribution to downward ir radiation flux

\[
\begin{align*}
truecloud &= 1. - ((trans(i) - 0.251) / 0.509) \\
fira(i) &= (1. - truecloud) \times ea \times stef \times (ta(i) - dtair) ** 4 + \\
&> truecloud \times ec \times stef \times (ta(i) - dtcloud) ** 4
\end{align*}
\]

c c

c reset snow and rain rate to zero

c
\[
\begin{align*}
snowa(i) &= 0.0 \\
raina(i) &= 0.0
\end{align*}
\]

c c

c for rain / snow partitioning, make it all rain if
c ta > 2.5 C and all snow if ta <= 2.5 C
c
c reference:
c
c Auer, A. H., 1974: The rain versus snow threshold temperatures,
c Weatherwise, 27, 67.
c
c IF (ta(i)-273.15 .GT. 2.5) THEN
  raina(i) = precip(i) / 3600.0
  IF(i .EQ. 1 .AND. raina(1) .GT. 0) THEN
  ENDIF
ELSE
  snowa(i) = precip(i) / 3600.0
  IF(i .EQ. 1 .AND. snowa(1) .GT. 0) THEN
  ENDIF
ENDIF

c
 c ---------------------------------------------------------------
c * * * irrigation calculations * * *
c ---------------------------------------------------------------
c
c reset rate of irrigation application per timestep
c
 xirriga(i) = 0.0

c if precipitation event - then no irrigation that day
c
 IF (time.GE.starti .AND. time.LT.endi > .AND. irrigate .EQ. 1 > .AND. precip(i) .EQ. 0.00) THEN
c
  xirriga(i) = xirrig(i) / ilens

c c update annual total - totirrig
c c rate of irrigation
c c multiplied by length of timestep (mm/s * s) = total applied
c c for this timestep
c
totirrig(i) = totirrig(i) + (xirriga(i) * dtime)
c
 ENDIF

c 100 CONTINUE
c
SUBROUTINE dailyMetCalc (imonth, iday, clear)

IMPLICIT NONE

INTEGER imonth,
   > iday,

! loop indice
! check if gdd needs clearing

IF (clear .EQ. 1) THEN

CALL CONST (tcthis, npoi, 100.0)
CALL CONST (twthis, npoi, -100.0)

CALL CONST (gdd0this, npoi, 0.0)
CALL CONST (gdd5this, npoi, 0.0)
CALL CONST (gdd0cthis, npoi, 0.0)
CALL CONST (gdd8cthis, npoi, 0.0)
CALL CONST (gdd10cthis, npoi, 0.0)

c initialize this year's value of npp and soil/plant gdds
    for non multi-year crops
    DO 20 i = 1, npoi
        DO 50 j = 1, npft
            IF (j .LE. scpft-1) THEN ! natural vegetation
                ayanpp(i,j) = 0.0
            ELSE IF (croplive(i,j) .EQ. 0 .AND. j .GE. scpft) THEN
                gddplant(i,j) = 0.0
                gddtsoi(i,j) = 0.0
                ayanpp(i,j) = 0.0
            ENDIF
        50 CONTINUE
    20 CONTINUE
    c
    ENDIF

c ----------------------------------------------------------------------
    c * * * set daily climatic variables for entire domain * * *
    c ----------------------------------------------------------------------
    c
    DO 200 i = 1, npoi
    c
    c calculated temperature extremes -- for vegetation limits (deg c)
    c for this purpose, use the 10-day running mean temperature
    c
tcthis(i) = MIN (tcthis(i), (a10td(i) - 273.16))
twthis(i) = MAX (twthis(i), (a10td(i) - 273.16))
    c
    c update this year's growing degree days
    c
gdd0cthis(i) = gdd0cthis(i) + MAX (0.0 , (td(i) - 273.16))
gdd0cthis(i) = gdd0cthis(i) + MAX (0.0 , (td(i) - 273.16)) ! wheat
gdd5cthis(i) = gdd5cthis(i) + MAX (0.0 , (td(i) - 278.16))
gdd8cthis(i) = gdd8cthis(i) + MAX (0.0 , (td(i) - 281.16)) ! maize
gdd10cthis(i) = gdd10cthis(i) + MAX (0.0 , (td(i) - 283.16)) ! soybean
    c
    c accumulate soil/plant growing degree days for planted crops
    c
DO 150 j = scpft, ecpft
   c for crops except winter wheat
   c
   IF (croplive(i,j) .EQ. 1.0 .AND. iwheat .NE. 2) THEN
   c
      gddplant(i,j) = gddplant(i,j) + MAX(0.0, MIN(td(i)
         > - baset(j), mxtmp(j)))
   c
      gddtsoi(i,j) = gddtsoi(i,j) + MAX(0.0, MIN(tsoi(i,1)
         > - baset(j), mxtmp(j)))
   c
   ELSE IF (croplive(i,j) .EQ. 1.0 .AND. iwheat .EQ. 2) THEN
   c
      gddplant(i,j) = gddplant(i,j) + vf(i) * MAX(0.0, MIN(td(i) - baset(j), mxtmp(j)))
   c
      gddtsoi(i,j) = gddtsoi(i,j) + vf(i) * MAX(0.0, MIN(tsoi(i,1) - baset(j), mxtmp(j)))
   c
   END IF
   c
   150 CONTINUE
   c
   200 CONTINUE
   c
   RETURN
   END
BIBLIOGRAPHY


Burns, K. (2010), personal communication.


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