Ammar Wahbi · Lee Heng
Gerd Dercon

Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent

IAEA
Joint FAO/IAEA Programme
Nuclear Techniques in Food and Agriculture

Springer Open

Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent

Ammar Wahbi • Lee Heng • Gerd Dercon

Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent

Springer Open

Joint FAO/IAEA Programme
Nuclear Techniques in Food and Agriculture

Ammar Wahbi
FAO/IAEA Division of Nuclear Techniques
Soil and Water Man & Crop
Nutrition Laboratory
Seibersdorf, Austria

Lee Heng
FAO/IAEA Division of Nuclear Techniques
Soil and Water Man & Crop
Nutrition Section
Vienna, Austria

Gerd Dercon
FAO/IAEA Division of Nuclear Techniques
Soil and Water Man & Crop
Nutrition Laboratory
Seibersdorf, Austria

ISBN 978-3-319-69538-9 ISBN 978-3-319-69539-6 (eBook)
https://doi.org/10.1007/978-3-319-69539-6

Printed on acid-free paper

This Springer imprint is published by the registered company Springer International Publishing AG part of Springer Nature.
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Foreword

The International Atomic Energy Agency (IAEA) and the Food and Agriculture Organization of the United Nations (FAO), through the Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture, assist scientists and farmers worldwide to ensure food security and promote sustainable agricultural resources. The Joint FAO/IAEA Division's programme and activities are demand-driven and focus on developing and transferring technologies in response to real and practical needs. This programme provides assistance to member states in the implementation of suitable nuclear and related techniques, where these have a competitive advantage to enhance, improve or increase agricultural production.

This publication was developed as a practical guideline for the estimation of fresh standing crop biomass and its water equivalent for incorporation into the calibration process of the novel soil moisture sensing technology known as the cosmic ray neutron sensor (CRNS). This publication was created to augment the IAEA TECDOC publication # 1809 which provides general instruction on the use, calibration and validation of the CRNS technology. This publication was created to be open access as to ensure accessibility for the wide scientific community. The specific intent of the following publication is to provide an introduction to three primary strategies for biomass estimation, an explanation of the advantages and disadvantages of each, incorporation of data into the CRNS calibration process and discussion of potential applications. This work is intended to serve as a referencing guide and synthesis of information regarding the estimation of crop biomass.

The Joint FAO/IAEA Division wishes to thank all contributors of its Soil and Water Management and Crop Nutrition Subprogramme and the University of Nebraska-Lincoln, involved in the preparation of this publication. The IAEA officers responsible for this publication were A. Wahbi, G. Dercon, L. Heng and W. Avery of the Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture.

A. Wahbi
G. Dercon
L. Heng
W. Avery

Editorial Note

The views expressed do not necessarily reflect those of the IAEA, the governments of the nominating member states or the nominating organizations.

The use of particular designations of countries or territories does not imply any judgement by the publisher, the IAEA, as to the legal status of such countries or territories, of their authorities and institutions or of the delimitation of their boundaries.

The depiction and use of boundaries, geographical names and related data shown on maps do not necessarily imply official endorsement or acceptance by the IAEA.

The mention of names of specific companies or products (whether or not indicated as registered) does not imply any intention to infringe proprietary rights, nor should it be construed as an endorsement or recommendation on the part of the IAEA.

The authors are responsible for having obtained the necessary permission for the IAEA to reproduce, translate or use material from sources already protected by copyrights.

Guidance provided here, describing good practices, represents expert opinion but does not constitute recommendations made on the basis of a consensus of member states.

Contents

Chapter 1
Introduction

A. Wahbi and W. Avery

1.1 Background

To meet the challenge of food security in the twenty-first century, global agricultural output must be increased. This will put pressure on already strained surface and groundwater resources. The incorporation of new techniques and technologies into agricultural resource management has the potential to improve the ability of farmers, scientists, and policymakers in assuring food security. The Soil and Water Management and Crop Nutrition Subprogramme of the Joint FAO/IAEA Division focuses on the development of improved soil, water, and crop management technologies and practices for sustainable agricultural intensification through the use of nuclear and conventional techniques.

Nuclear and related techniques can help develop climate-smart agricultural practices by optimizing water use efficiency. The cosmic ray neutron sensor (CRNS) is one such novel technology capable of estimating soil moisture on a field scale (approx. 20 ha), through the detection of hydrogen within soil H_2O molecules. This helps fill the need for spatial soil moisture information left by common point-based sensors. Due to the nature of the CRNS technique as a detector of hydrogen mass changes, a calibration function is included within its methodology designed to quantify other sources of environmental hydrogen that can introduce error into the CRNS signal.

A. Wahbi (✉)
FAO/IAEA Division of Nuclear Techniques, Soil and Water Man & Crop, Nutrition Laboratory, Seibersdorf, Austria
e-mail: a.wahbi@iaea.org

W. Avery
Soil and Water Management & Crop Nutrition Subprogramme, Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture, International Atomic Energy Agency, Vienna, Austria
e-mail: w.avery@iaea.org

A. Wahbi et al., *Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent*, https://doi.org/10.1007/978-3-319-69539-6_1

The estimation of crop biomass is important in the proper calibration of a CRNS. More importantly, the proportion of water within growing crop vegetation, also known as the biomass water equivalent (BWE), is a significant source of detected hydrogen within the footprint of the CRNS that must be separated from the overall signal to isolate the contribution of soil moisture. Traditional methods of estimating biomass involve the physical harvesting of plants in a field upon which they are weighed for their mass, dried, and weighed again to determine weight percent of water. While this method is accurate on a plant by plant scale, spatial heterogeneity is difficult to quantify without extensive and time-consuming sampling campaigns across a field. Addressing the issue of landscape-scale heterogeneity in crop biomass can be challenging. However, the use of satellite-based remote sensing techniques has the potential to overcome the problems inherent with destructive sampling. Images of the surface of the Earth can be analyzed for light reflectance. These data have strong relationships to biomass on the surface and as such can be used in lieu of destructive sampling. Additionally, the measurement of neutrons via the CRNS itself has potential for estimating plant biomass (and eventually BWE) through relationships between CRNS calibration parameters and BWE. Moreover, preliminary work indicates BWE is strongly correlated to the widely used crop coefficient (kc).

1.2 Scope

This publication focuses on the quantification of living agricultural crop biomass. Specifically, three techniques are detailed: traditional in situ destructive sampling, satellite-based remote sensing of plant surfaces, and biomass estimation via the use of the CRNS itself (specifically the ratio of fast to thermal neutrons). The advantages and disadvantages of each method are discussed along with step by step instructions on proper procedures and implementation. This publication was developed as a partial output of the Coordinated Research Project titled “Landscape Salinity and Water Management for Improving Water Productivity” managed by the Soil and Water Management and Crop Nutrition Subprogramme of the Joint FAO/IAEA Division.

1.3 Structure

This publication is intended to serve as a guideline for scientists, technicians, and students and provides a description of the key characteristics of each technique, an example of proper use, and a discussion of potential applications.

This publication is divided into four chapters. Chapter 1 introduction. Chapter 2 discusses the procedures for estimating crop biomass via in situ destructive plant sampling as well as subsequent analysis. Chapter 3 discusses the use of satellite-based remote sensing as a means of crop biomass estimation and provides a step by step guideline for data acquisition and analysis. Chapter 4 examines the use of the CRNS itself (ratio of thermal to fast neutron counts) as a tool for the estimation of biomass and BWE.

Chapter 2
In Situ Destructive Sampling

A. Wahbi and W. Avery

2.1 The Concept of Representivity

When designing experiments, environmental scientists face the challenge of how to accurately represent nature. The idea of sampling patterns and strategies truly reflecting research variables is intrinsic to scientific pursuits. This is particularly true in environmental science due to the complex heterogeneity present in nature. It is vitally important in most studies for researchers to account for natural variations in soil, air, water, and vegetation that can change in space and time. Many strategies focus on the use of strategically placed transects or plot-based sampling campaigns designed to include as many aspects of a particular variable as possible within a study area. Determining how many samples must be taken, whether they are of soil, plant matter, water, etc., depends entirely on the balance of time, effort, and cost while in the field. As a rule of thumb, the more samples that can be gathered correctly, the more trustworthy eventual results will be. Unfortunately, environmental sampling can be time-consuming and expensive depending on its location or the procedures for its procurement. This is one of the reasons why the use of satellite-based remote sensing, computer modeling, and proximal sensing has gained popularity within the scientific community in recent decades. However, the heterogeneity and scale of the environment again make large spatial-scale research difficult and often require in situ validation campaigns to

A. Wahbi (✉)
FAO/IAEA Division of Nuclear Techniques, Soil and Water Man & Crop, Nutrition Laboratory, Seibersdorf, Austria
e-mail: a.wahbi@iaea.org

W. Avery
Soil and Water Management & Crop Nutrition Subprogramme, Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture, International Atomic Energy Agency, Vienna, Austria
e-mail: w.avery@iaea.org

A. Wahbi et al., *Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent*, https://doi.org/10.1007/978-3-319-69539-6_2

ensure data quality. This is one of the main advantages of the use of the CRNS, due to the significant spatial and temporal variations soil moisture can exhibit.

2.2 Plant Sampling Pattern and Design

The calibration process for the CRNS technique has been extensively detailed and is a prime example of controlling for heterogeneity within agricultural environments [1–6]. The CRNS calibration function first proposed by Desilets et al. [1] is designed primarily around a sampling structure within the circular footprint of the instrument (circle of radius ~ 250 m). Specifically, 18 sampling sites are distributed on six transects located every 60° within the circle. Along each transect three sampling sites are located at 25, 75, and 200 m from the center point (usually where the CRNS is located; see Fig. 2.1).

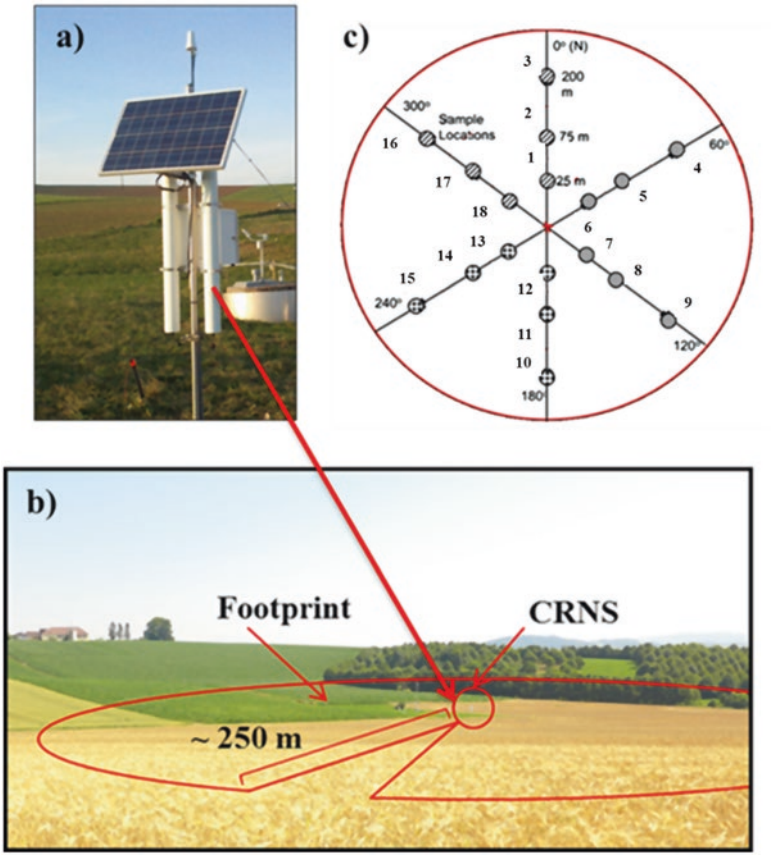


Fig. 2.1 Depiction of a stationary CRNS (**a**), its footprint on the landscape (**b**), and calibration sampling pattern (**c**)

2.2.1 *Sampling Instructions*

Along with soil samples, plant samples are taken at each of the 18 sampling sites. The following is a step by step guide for proper in situ destructive sampling:

Step One: Randomly select one to three individual plants (depending on crop size, large plants such as fully grown maize may be impractical to remove three individuals) spaced apart from each other, and pull them from the ground as to preserve as much root structure as possible.

Step Two: Shake any loose soil from the bottom of the plant so only the plant itself remains.

Step Three: Place the entire plant into a brown paper bag (or other containers) labeled appropriately (i.e., plants 1–3, point numbers 1–18; see Fig. 2.1); be careful to minimize folding or breaking of the plant cellular structure during removal and placement into the bag as to minimize any water loss.

Step Four: Fill back each hole left by the removed plants and repeat process at each of the 18 sampling locations collecting one to three plants at each site.

2.3 Biomass Water Equivalent

Fundamentally, the CRNS detects all environmental hydrogen within its footprint including hydrogen in soil moisture water molecules (see Fig. 2.2). As such, the primary component of crop biomass that introduces error to the CRNS signal is cellular water.

The term biomass water equivalent (BWE, mm of H_2O) is used in the CRNS calibration functions to describe the equivalent amount of water that would be required to introduce the same amount of water as a particular type of living crop biomass. It is defined as follows (Eq. 2.1) where *SWB* and *SDB* stand for standing wet and dry biomass, respectively, (kg/m^2) and f_{WE} = 0.494 which is the stoichiometric ratio of H_2O to organic carbon molecules in the plant (assuming this is mostly cellulose $C_6H_{10}O_5$) [4, 5]. Note: the units in the following equation are mass per unit area which is equivalent to a depth of water. During destructive sampling between one and three plants are removed. As such, an average plant density must be known to calculate into kg/m^2 or mm H_2O (i.e., by dividing by the density of water = 1000 kg/m^3 and multiplying by 1000 to convert m to mm). The plant density can be estimated by laying down a quadrat (i.e., a square of dimensions 50×50 cm, 1×1 m, etc. made of PVC) and counting the number of plants inside the encompassed area.

$$\mathrm{BWE}=SWB-SDB+SDB*f_{WE} \tag{2.1}$$

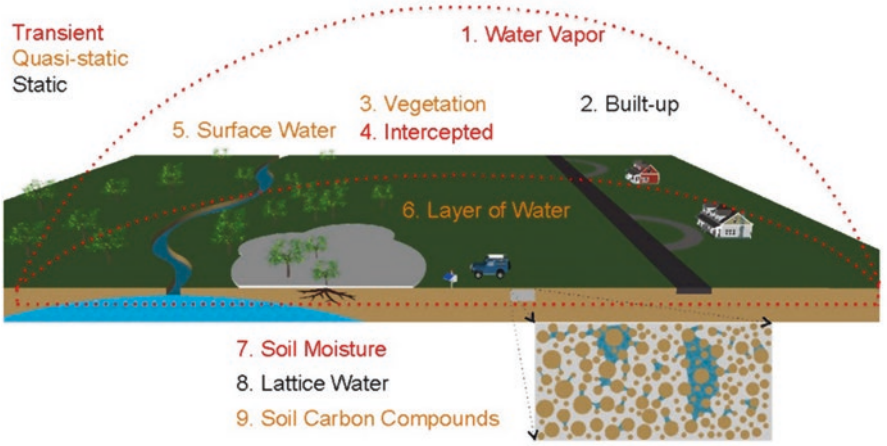


Fig. 2.2 Depiction of environmental hydrogen sources including those that change and do not change in time

2.3.1 Processing Instructions

After initial in situ collection, time becomes a highly relevant factor due to the water loss freshly harvested biomass samples experience immediately upon removal from the field. The following is a step by step guide on the proper weighing and oven-drying protocols for the determination of BWE:

Step One: Weigh biomass samples while they are still full of water as soon as possible from the time of their removal from the soil. This should be done with the plants in a container placed on the scale after zeroing. This can be difficult with fully grown maize plants but can be done if the plant is folded or cut within the container until it fits and then promptly weighed.

Step Two: Dry the plants in a standard convection drying oven at 70 ° C for 120 h (can check mass at 96 h and 120 h to make sure it is not changing by more than 1% between time intervals; otherwise, continue for an additional 24 h).

Step Three: Remove dried plants and weigh them once more.

2.4 Conclusions

The calibration process for the CRNS technique involves in situ sampling of biomass designed to quantify the hydrogen in its cellular structure and the water within. Traditional destructive biomass sampling is employed in a radial sampling pattern controlling for spatial variability of soil, water, and vegetation characteristics. This section provides detailed descriptions of biomass sampling procedures and the

determination of BWE. The main limitation of this form of sampling is its time-consuming nature and therefore is limited to a few fields at a time. This works well for stationary CRNS locations where the BWE must be calculated for one singular field but becomes difficult when mobile versions of the CRNS technique are employed in which the BWE must be determined for many fields (see Franz et al. (2015) and Avery et al. (2016) for more details on the mobile aspects of this technology [4, 5]).

References

1. Desilets D, Zreda M, Ferré TPA (2010) Nature's neutron sensor: land surface hydrology at an elusive scale with cosmic rays. Water Resour. Res. 46:W11505
2. Zreda M, Schuttleworth WJ, Zeng X, Zweck C, Desilets D, Franz T, Rosolem R (2012) COSMOS: the cosmic ray soil moisture observing system. Hydrol Earth Syst Sci 16:4079
3. Franz TE, Zreda M, Ferre PA, Rosolem R, Zweck C, Stillman S, Zeng X, Shutt WJ (2012) Measurement depth of the cosmic ray soil moisture probe affected by hydrogen from various sources. Water Resour Res 48:W08515
4. Franz TE, Wang T, Avery W, Finkenbiner C, Brocca L (2015) Combined analysis of soil moisture measurements from roving and fixed cosmic ray neutron probes for multiscale real-time monitoring. Geophys Res Lett 42:3389
5. Avery WA, Finkenbiner C, Franz TE, Wang T, Nguy-Robertson AL, Suyker A, Arkebauer T, Munoz-Arriola F (2016) Incorporation of globally available datasets into the roving cosmic ray neutron probe method for estimating field-scale soil water content. Hydrol Earth Syst Sci 20:3859
6. Franz TE, Wahbi A, Vreugdehil M, Weltin G, Heng L, Oismueller M, Strauss P, Dercon G, Desilets D (2016) Using cosmic ray neutron probes to monitor landscape scale soil water content in mixed land use agricultural ecosystems. Appl Environ Soil Sci 2016:11

Chapter 3
Remote Sensing via Satellite Imagery Analysis

W. Avery

3.1 Photo-Reflective Properties of Plants

Healthy green vegetation absorbs red and blue light wavelengths preferentially for use in photosynthesis. Green light (wavelength 545–565 nm), however, is mostly reflected leading to the green appearance of living biomass. This characteristic coincides with interactions outside the visible portion of the electromagnetic spectrum. Near-infrared (NIR, wavelength 841–876 nm) light also interacts with healthy vegetation in a slightly different way. The presence of chlorophyll in green vegetation does not utilize green light due to properties of the molecules themselves and the harnessing of energy by the plant. NIR light is reflected mainly due to the physical structure of healthy leaf tissue (see Fig. 3.1 for a representation of these phenomena). These characteristics are not static in time, as plants continue to develop and transition through their life cycle; they eventually loose leaf structure and chlorophyll concentrations for many reasons including seasonal changes, disease, age, water scarcity, etc. These realities change the relationship between vegetation and light. This is particularly apparent in agricultural systems where plants undergo a predictable transition from planting to maturity and eventually senescence at the end of the growing season. This senescence is characterized mainly by a loss of chlorophyll, a collapse of leaf structure, and an investment by the plant of resources into the production of fruiting bodies and grain. These principles are the basis for much of remote sensing within agricultural ecosystems.

W. Avery (✉)
Soil and Water Management & Crop Nutrition Subprogramme, Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture, International Atomic Energy Agency, Vienna, Austria
e-mail: w.avery@iaea.org

A. Wahbi et al., *Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent*, https://doi.org/10.1007/978-3-319-69539-6_3

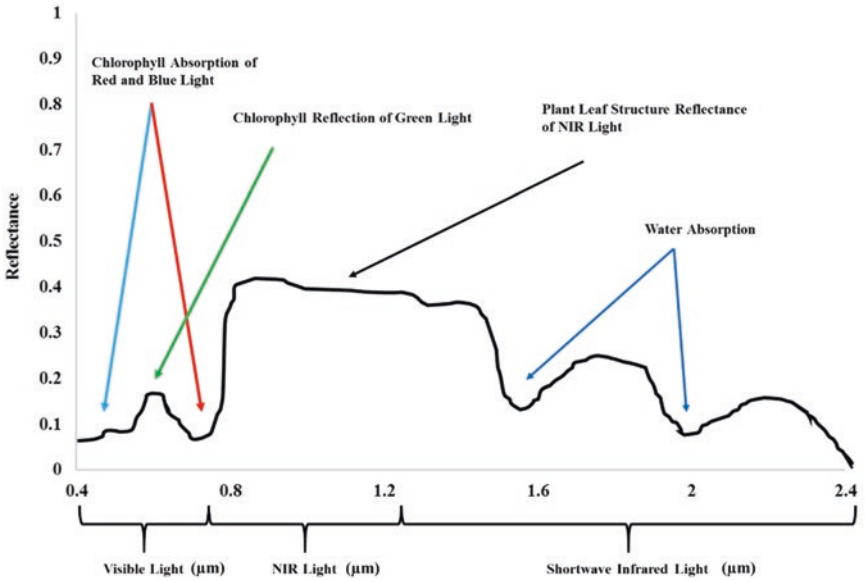


Fig. 3.1 Representation of green leaf reflectance across the electromagnetic spectrum, note the absorption of red and blue light for use in photosynthesis

3.1.1 Imaging Fields and Landscapes with Satellites

Satellite-based remote sensing relies on the principles of plant light reflectance previously described. Scientists can freely access data provided by the US National Aeronautics and Space Administration as well as the European Space Administration. These agencies maintain many different satellites that are capable of detecting and producing a large variety of energy and light. The majority of remote sensing relies on the detection of reflected sunlight from the Earth's surface and has applications in many disciplines. The primary advantage of remote sensing as a technique is based on the large spatial scale inherent to a space-borne sensor. This is particularly true for environmental scientists who seek to understand large-scale processes and patterns. Typical procedures for remote sensing studies involve image acquisition from the particular agency responsible for the chosen satellite, followed by subsequent image analysis of study sites (usually done via computer coding or special software such as ArcGIS), and lastly results are analyzed and conclusions drawn.

3.1.2 Vegetation Indices

One of the primary remote sensing metrics used by environmental scientists to study nature is what is known as a vegetation index. A vegetation index is a mathematical formula that relates two or more quantities of reflected light to determine characteristics of the land surface. The first index to be developed, and arguably the most

commonly used, is known as the Normalized Difference Vegetation Index (NDVI), given here, where NIR stands for near infrared and VIS for visible light, respectively:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{VIS})}{(\mathrm{NIR} + \mathrm{VIS})} \tag{3.1}$$

This equation has been used for decades [1] to serve as a measure of the health of observed vegetation. This remains true today, although many improvements and alterations have been made to this basic formula over the decades.

3.2 Satellite Image Analysis

As mentioned in Sect. 2.3, the CRNS detects all forms of hydrogen within its footprint (Fig. 2.2). This includes the hydrogen contained within green growing biomass. As such, biomass water equivalent must be quantified within the footprint of any CRNS deployed in the field for proper calibration to be achieved. Studies have shown that vegetation indices derived from satellite remote sensing images can be used to reliably estimate agricultural biomass [2–4]. This has recently been expanded upon in the context of the CRNS calibration function. Avery et al. [2] demonstrated that the use of satellite-based remote sensing can be used to determine biomass within agricultural systems through the use of vegetation indices. It is from this study that the following procedures are derived. Satellite imaging eliminates the need for time-consuming and difficult in situ sampling campaigns. Moreover, remote sensing provides the most feasible solution for support of mobile CRNS devices to monitor soil moisture over larger areas without the need for extensive multi-field in situ sampling campaigns.

As detailed in Nguy-Robertson and Gitelson [3] and Nguy-Robertson et al. [4], the best known relationship to date between a vegetation index and actual biomass for maize and soybean as determined by in situ experiments is the Green Wide Dynamic Range Vegetation Index (GrWDRVI). Its formula is a modified version of the classic NDVI (Eq. 3.1) developed in an effort to improve the statistical relationship between satellite data and surface biomass (determined via destructive sampling) [5]. The equation is given here, note that NIR (wavelength 841–876 nm) stands for near-infrared light and Green (wavelength 545–565 nm) for green light:

$$\mathrm{GrWDRVI} = \left(\frac{0.1 * \mathrm{NIR} - \mathrm{Green}}{0.1 * \mathrm{NIR} + \mathrm{Green}} \right) \tag{3.2}$$

The following is a step by step guide for determining standing wet biomass (to be used for determining BWE) via satellite image analysis for use in the CRNS calibration function (see Eq. 2.1). This index calculates wet biomass but not dry biomass. As such, the use of remote sensing in this publication to calculate the BWE is dependent on knowledge of crop growth stage and/or existing crop models that can give an estimate of the ratio of water mass to dry mass within the plant. It is impor-

tant to note that these procedures use images produced by NASA's Terra satellite (http://earthexplorer.usgs.gov/), specifically the 500 m resolution Moderate Resolution Imaging Spectroradiometer (MODIS).

Step One: Pick a study area.

Step Two: Navigate online to http://earthexplorer.usgs.gov/, this is the website that will provide the downloadable images from many different satellites including Terra. This website and data are free to access, but one must create an account initially.

Step Three: The website will present with a map of the Earth. This map can be navigated and examined down to a field scale to find any particular study site or sites a researcher may be interested in. Select the study site(s) by clicking on the map to place a point and then clicking another point to connect them with a line. Continue placing points until the area between the points has been created upon which your area has been delineated.

Step Four: Once your study area has been selected, press the blue "data sets" button on the bottom left. This will bring up a list of available datasets for the specific study area that was defined in step three. Navigate to the tab titled: "NASA LPDAAC Collections" and expand the drop-down list. Click the drop-down list next to the option titled: "MODIS Land Surface Reflectance." Select the check box next to the first option: "MOD09A1" this is the global land surface reflectance taken every 8 days at a 500 m spatial scale.

Step Five: Once the data has been chosen, thumbnail images will appear on the left with the top image being the most recent. These images correspond to the days that the satellite passed over the selected study area on an 8-day rotation. To choose which days to download, simply click the "download options" button and select "HDF Format."

Step Six: Once the data have been downloaded onto the computer, place the HDF files into a folder with an appropriate title. This will serve as a source for the computer to look for files to process.

Note: The following steps require the use of three pieces of software:

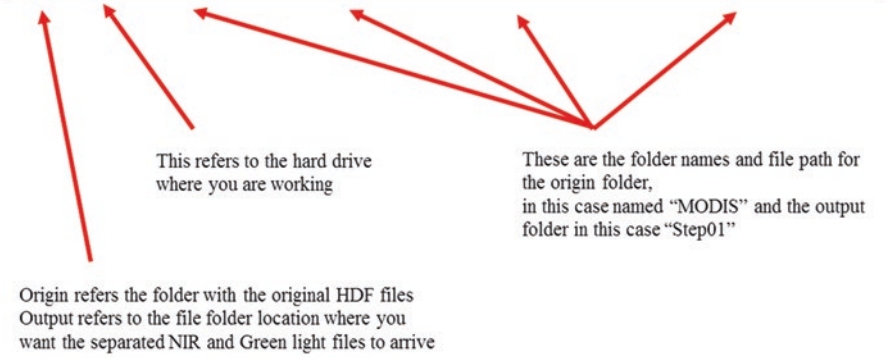
1. ArcGIS, or similar image processing software (not an open-source software).
2. IDLE (Integrated Development and Learning Environment): this is an open-source user interface software designed to be used with the computer coding language Python which serves as the basis for MODIS image processing in this publication. It is important to mention that other computer coding languages, imaging software, or user interfaces can be used if so desired but will likely require changes to the code or other adaptations by a qualified scientist.
3. Python: this is a computer coding language that can be freely accessed via the internet (open source).

Step Seven: Once the HDF raw files are in the correct folder, the following Python code (denoted in the outlined boxes) should be entered into IDLE (windowed user interface where code is to be written); this code is very sensitive to indentations (note: this code was developed by Dr. Anthony Nguy-Robertson while at the University of Nebraska-Lincoln), and file names are merely an example and must be replaced with the names chosen in any study following this guide.

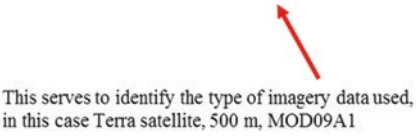
The purpose of this step is to extract the NIR and Green light into separate files from the overall reflectance data for further processing.

This code serves to identify the file location and file types to be used in the image analysis process:

```
origin = "E:\\Williams Projects\\Cosmic Ray Project 2014\\COSMOS Rover Calibration\\MODIS\\"
output = "E:\\Williams Projects\\Cosmic Ray Project 2014\\COSMOS Rover Calibration\\MODIS\\Step01\\"
```




```
try:
    import arcpy, os
    arcpy.env.workspace = origin
    files_Te500= arcpy.ListRasters("MOD09A1*")
```



This code serves to extract the individual NIR and Green light wavelengths for further processing via the GrWDRVI equation and ultimately into standing wet biomass (SWB):

```
for i in range(len(files_Te500)):
    text = ("Terra_"+str(files_Te500[i])[9]+str(files_Te500[i])[10]+
        str(files_Te500[i])[11]+str(files_Te500[i])[12]+"_"+
        str(files_Te500[i])[13]+str(files_Te500[i])[14]+str(files_Te500[i])[15])
    print text

    try:
      if arcpy.Exists(output+text+"_flag.tif"):
        print "Quit wasting my time! Flag Exists!"
      else:
        arcpy.ExtractSubDataset_management(files_Te500[i], output+text+"_flag.tif", "11")
        print "Flag successful"
    except:
      print "Unfortunately, casulties were the result of this extraction."

    try:
      if arcpy.Exists(output+text+"_NIR.tif"):
        print "NIR Exists!"
      else:
        arcpy.ExtractSubDataset_management(files_Te500[i], output+text+"_NIR.tif", "1")
        print "NIR successful"
    except:
      print "Unfortunately, casulties were the result of this extraction."

    try:
      if arcpy.Exists(output+text+"_Green.tif"):
        print "Green Exists!"
      else:
        arcpy.ExtractSubDataset_management(files_Te500[i], output+text+"_Green.tif", "3")
        print "Green successful"
    except:
      print "Unfortunately, casulties were the result of this extraction."
    print str(i+1)+" of "+str(len(files_Te500))+" files completed"
```

This code serves to alert the user when the processing described above is successful or unsuccessful:

```
import winsound
  winsound.PlaySound("SystemExit", winsound.SND_ALIAS)
  winsound.PlaySound("*", winsound.SND_ALIAS)
  print "Your files are finished processing successfully"
except:
  print "Your files failed to extract sucessfully."
  print arcpy.GetMessages()
```

Note: Before the code is shown, it must be stated that a text file (.txt) must be present in the folder containing the newly processed NIR and Green reflectance files created from the previous code. This .txt file must be placed alongside these files as a reference for the next section of code to properly eliminate incidental cloud cover.

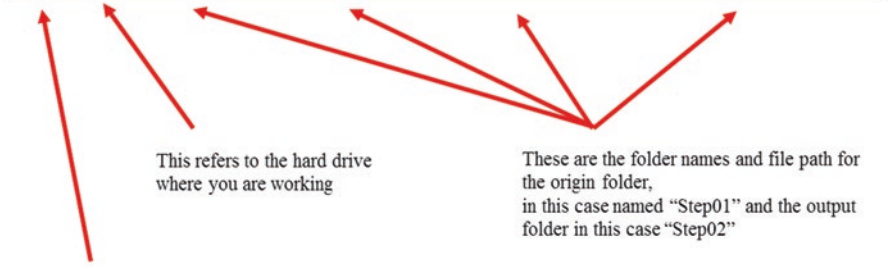
The .txt file needs to contain these numbers exactly as shown:

```
0 7 : 1
7 8 : 0
8 71 : 1
71 72 : 0
72 135 : 1
135 136 : 0
136 100000 : 1
```

Step Eight: Once the code outlined in step seven has been written into IDLE, and has run correctly (Python code in IDLE can be activated by clicking the drop-down box on the top left of the window and selecting "run module"), then the next piece of code can be written. This step should have its code written into a new IDLE file (not the same as the previous step seven code). The following code is intended to remove files that correspond to days with incidental cloud cover; this is for the purpose of data quality control.

This code serves to locate the recently processed files from step seven and signify where they will be placed upon the next step:

```
origin = "E:\\Williams Projects\\Cosmic Ray Project 2014\\COSMOS Rover Calibration\\MODIS\\Step01"
output = "E:\\Williams Projects\\Cosmic Ray Project 2014\\COSMOS Rover Calibration\\MODIS\\Step02\\"
```



Origin refers the folder with the separated NIR and Green reflectance data files
Output refers to the file folder location where you
want the separated NIR and Green light files now corrected for cloud cover to arrive

This code serves to remove files that have been downloaded corresponding to days with heavy cloud cover (this can skew the results by changing light reflectance to the satellite):

```
try:
    import arcpy, os
    from arcpy import env
    from arcpy.sa import *
    arcpy.env.workspace = origin
    arcpy.CheckOutExtension('Spatial')
    ## Determines all the files needed to process ##
    files_flag = arcpy.ListRasters("Te*flag*")
    files_reclasstext = arcpy.ListFiles("reclass_range.txt")
    #print files_flag
    for i in range(len(files_flag)):
        ## For Naming Files ##
        text = str(files_flag[i])[0]
        for j in range(1,14):
            text = text+str(files_flag[i])[j]
        text_reclass = text+"_reclass.tif"
        text_buffer = text+"_bflag.tif"
        print text_buffer
        print text_reclass
        print files_reclasstext
        ## Buffer around cloud pixels to help reduce 'bad' pixels in analysis##
        try:
            if arcpy.Exists(output+text_buffer):
                print "Stop wasting my time!!!!"
            else:
                ## First the 16-bit QA needs to be reclassified to make ##
                ## it easier to identify cloud-contaminated pixels ##
                ## https://lpdaac.usgs.gov/products/modis_products_table/myd09a1 ##
                ## ##
                #print origin+files_flag[i]
                arcpy.CalculateStatistics_management(files_flag[i])
                print text_reclass
                print files_flag[i]
                print files_reclasstext[0]
                outRas = ReclassByASCIIFile(files_flag[i],files_reclasstext[0])
                print text_reclass
                outRas.save(origin+text_reclass)
                print "Created the 0's and 1's for expansion!"
                ## The 2 refers to the number of pixels to expand which is ##
                ## approximently 1 km for 500 m MODIS imagery ##
                ## The '[1] refers to the flags identified above ##
                outRas = Expand(text_reclass,2,[1])
                outRas.save(output+text_buffer)
                ## You can always edit my snarky and probably not so ##
                ## humourous 'Is it working?' progress comments ##
                print "I beleve those clouds are expanding!"
        except:
            print "Lack of humidity! Check your files!"
        print str(i+1)+" of "+str(len(files_flag))+" files completed"
```

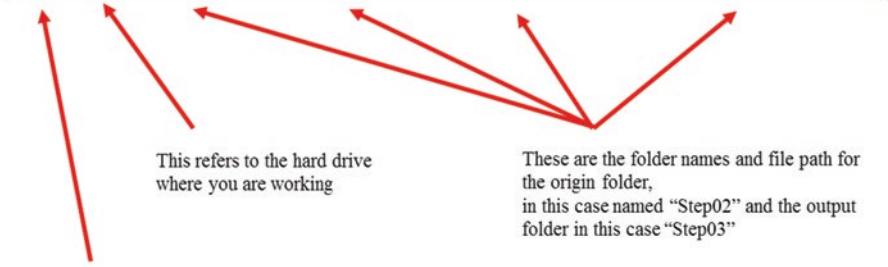
This code serves to alert the user if the process was successful via a message and a sound:

```
import winsound
   winsound.PlaySound("SystemExit", winsound.SND_ALIAS)
   winsound.PlaySound("*", winsound.SND_ALIAS)
   print "Your files are finished processing successfully"
except:
   print "Your files failed to process sucessfully."
   print arcpy.GetMessages()
```

Step Nine: Once the code removing incidental cloud cover has been run, the next piece of code can be written. This code should be written in a new IDLE file separate from the previous two. The purpose of this next section of code is to process the separated NIR and Green light reflectance files that have now been corrected for days of heavy cloud cover, into the vegetation index detailed in Sect. 3.2 (Eq. 3.2).

This code serves to locate the recently processed files from step eight and signify where they will be placed upon the next step:

```
origin = "E:\\Williams Projects\\Cosmic Ray Project 2014\\COSMOS Rover Calibration\\MODIS\\Step02"
output = "E:\\Williams Projects\\Cosmic Ray Project 2014\\COSMOS Rover Calibration\\MODIS\\Step03\\"
```



Origin refers the folder with the separated NIR and Green reflectance data files corrected for cloud cover
Output refers to the file folder location where you
want the Green Wide Dynamic Range Vegetation Index (GrWDRVI) to be placed

This code serves to calculate the GrWDRVI from the now separated NIR and Green light wavelength files created in step seven:

```
try:
    import arcpy, os
    from arcpy import env
    from arcpy.sa import *
    arcpy.env.workspace = origin
    arcpy.CheckOutExtension('Spatial')



########### Terra ########################
    ##  Determines files in each band   ##
    files_b4= arcpy.ListRasters("Te*Green*")
    files_b2= arcpy.ListRasters("Te*NIR*")
    files_flag = arcpy.ListRasters("Te*bflag*")

    for i in range(len(files_b2)):
        text = str(files_b2[i])[0]
        text2 = str(files_flag[i])[0]
        for j in range(1,14):
            text = text+str(files_b2[i])[j]
            text2 = text2+str(files_flag[i])[j]
        text_grwdrvi = text+"_grwdrvi.tif"
        text_grndvi = text+"_grndvi.tif"
        print text_grwdrvi
        print text_grndvi
        ##  Calculate VIs from TIFF while excluding clouds  ##

        try:
            if arcpy.Exists(output+text_grwdrvi):
                print "Quit wasting my time! Green WDRVI exists!"
            else:
                outRas = Con(Float(files_flag[i])==0,(0.1*Float(files_b2[i])-Float(files_b4[i]))/(0.1*Float(files_b2[i])+Float(files_b4[i]))+(1-0.1)/(1+0.1),-9999)
                outRas = SetNull(outRas < -1, outRas)
                outRas = SetNull(outRas > 4, outRas)
                outRas = SetNull(outRas == 0, outRas)
                outRas.save(output+text_grwdrvi)
                print "Success in ArcGIS is completed by processing one Green WDRVI file at a time."

        except:
            print "These bands did not play nice: Green WDRVI!  Check your files!"
```

The index used in this publication (GrWDRVI) was developed through many comparisons of actual biomass determined via destructive sampling and biomass values determined through satellite image analysis [3, 4]. This research yielded coefficients from linear statistical relationships between the two methods that allowed for a mathematical transformation of the GrWDRVI values (between 0 and 1) into biomass (kg/m^2). These biomass values are equivalent to "standing wet biomass" (SWB) and as such are used to determine biomass water equivalent for use in the CRNS calibration function (see Eq. 2.1) (Fig. 3.2).

Step Ten: Once the GrWDRVI values have been calculated, the resulting files should have been created as a TIFF image file (.tif). This file extension can be placed into image processing software such as ArcGIS in which individual GrWDRVI values will be visually represented as interlocking four-sided polygons that correspond to the spatial resolution of the satellite imagery. Here is a representation of what they look like:

Fig. 3.2 Representation of TIFF file output of the GrWDRVI detailed in steps seven and eight. Each polygon represents one index value (between 0 and 1)

Step Eleven: Locate the areas of interest in which the aforementioned polygons overlap. This is easiest to do by overlaying a basic satellite image of any particular study area. Once the appropriate areas have been located, use the "Identify" button (ArcGIS) or similar function if using any other image processing software, to identify the GrWDRVI value of each polygon that overlaps the area of interest. These numbers now can be averaged to determine the mean index value for each study site.

Step Twelve: The reflective behavior of plant material changes over the course of a growing season (see Sect. 2.1). This means that the linear relationship between biomass and the GrWDRVI changes from the beginning and peak of the growing season (denoted as "Green-Up" in this publication), to the end of the growing season (denoted as "Senescence" in this publication) [2–4]. Calculation of biomass must be done with separate equations to reflect the differences in each relationship. Additionally, GrWDRVI values below 0.25 are not to be used due to the fact that the biomass is too small during these growth stages and the satellite data cannot accurately predict plant biomass. Note: the equations are given here as derived from 11 years of observation from Nebraska, USA [2]:

$$\text{Maize Biomass Green} - \text{Up} = \frac{8}{\left(1 + \text{EXP}\left(-9.844 * \left(\text{GrWDRVI} - 0.501\right)\right)\right)} - 0.618 \tag{3.3}$$

$$\text{Maize Biomass "Senescence"} = -1.354\left(\text{GrWDRVI}\right)^{-1.351} + 8.817 \tag{3.4a}$$

$$\text{Maize Biomass Senescence} = 0.1348\left(\text{GrWDRVI}\right)^{-2.875} + 7.256 \tag{3.4b}$$

Note: Each equation contains coefficients developed for one particular crop type, in this case maize. These coefficients change for other crops, and new datasets comparing GrWDRVI values with in situ biomass estimates must be made for each and every crop type that is included in a study. Studies conducted by Nguy-Robertson and Gitelson [3] and Nguy-Robertson et al. [4] determined that maize exhibits different statistics when it exists in a rain-fed or irrigated setting. As such, Eqs. 3.4a and 3.4b correspond to rain-fed values and irrigated values, respectively. It is important to note that work conducted by Avery et al. (2016), Nguy-Robertson et al. (2012), and Nguy-Robertson and Gitelson (2015), [2–4] has produced the coefficients represented in the above equations within an agricultural environment in eastern Nebraska in the United States. These values can be used for studies in similar environments but will likely need to be tailored for use in different regions.

Step Eleven: Once standing wet biomass (SWB) values have been calculated (kg/m^2), they can be transformed into standing dry biomass (SDB) by either assuming fully grown maize is approximately 70–80% H_2O by weight or by referring to previous estimates of biomass water weight percent determined from in situ destructive sampling performed via procedures detailed in Chap. 2. Note that maize typically dries out to 25–30% by harvest. Now, BWE can be determined via Eq. 3.1 for use in the CRNS calibration functions.

3.3 Conclusions

This section summarizes the use of remote sensing for determining agricultural crop biomass. Additionally, it details step by step instructions on how to use remote sensing data to determine biomass and subsequently biomass water equivalent for use in the CRNS calibration process. The need for accurate biomass data is important for effective use of the CRNS technology within agricultural systems. However, eliminating or minimizing the need for time-consuming in situ destructive biomass sampling campaigns is also valuable for large-scale use of the CRNS method or its mobile versions making the incorporation of remote sensing a worthwhile endeavor.

References

1. Rouse JW, Scheel RH, Deering DW (1974) Monitoring vegetation systems in the great plains with ERTS. In: Proceedings, 3rd Earth Resource Technology Satellite (ERTS) symposium, vol 1, p 48
2. Avery WA, Finkenbiner C, Franz TE, Wang T, Nguy-Robertson AL, Suyker A, Arkebauer T, Munoz-Arriola F (2016) Incorporation of globally available datasets into the roving cosmic ray neutron probe method for estimating field-scale soil water content. Hydrol Earth Syst Sci 20:3859

3. Nguy-Robertson AL, Gitelson AA (2015) Algorithms for estimating green leaf area index in C3 and C4 crops for MODIS, Landsat TM/ETMC, MERIS, Sentinel MSI/OLCI, and Venus sensors. Remote Sens Lett 6:1336
4. Nguy-Robertson AL, Gitelson A, Peng Y, Viña A, Arkebauer T, Rundquist D (2012) Green leaf area index estimation in maize and soybean: combining vegetation indices to achieve maximal sensitivity. Agron J 104:360
5. Gietelson AA (2004) Wide dynamic range vegetation index for remote quantification of biophysical characteristics of vegetation. J Plant Physiol 161:165

Chapter 4
Estimation of Biomass Water Equivalent via the Cosmic Ray Neutron Sensor

T. E. Franz, A. Wahbi, and W. Avery

4.1 The Role of Biomass in the CRNS Calibration

The CRNS functions at its most fundamental level as a detector of the hydrogen within its area of influence (circle of radius ~ 250 m). As such, hydrogen other than that within the water molecules in the soil is detected. A series of calibration equations have been developed to quantify and eliminate these sources of hydrogen so that the signal of soil moisture can be isolated [1–6]. McJannet et al. [7] demonstrated that soil moisture is the largest contributor of hydrogen to the signal of the CRNS with growing biomass contributing only slightly. These data show that in an agricultural environment, the most significant source of error comes in the form of soil lattice water (i.e., hydrogen molecules integrated into mineral structures and bound water between mineral grains not released at oven drying temperatures of 105 °C for 24 h) and from water vapor in the atmosphere. Despite this, growing biomass if left unquantified remains a source of uncertainty that must be addressed, partly in fast-growing agricultural crops. Much of the current and past research into the CRNS in agricultural environments focuses on its use as a sensor of soil moisture. However, there have also been investigations into its use as a tool for estimating growing crop biomass itself [8,

T. E. Franz (✉)
School of Natural Resources, University of Nebraska-Lincoln, Lincoln, NE, USA
e-mail: Trenton.franz@unl.edu

A. Wahbi
FAO/IAEA Division of Nuclear Techniques, Soil and Water Man & Crop, Nutrition Laboratory, Seibersdorf, Austria
e-mail: a.wahbi@iaea.org

W. Avery
Soil and Water Management & Crop Nutrition Subprogramme, Joint FAO/IAEA Division of Nuclear Techniques in Food and Agriculture, International Atomic Energy Agency, Vienna, Austria
e-mail: w.avery@iaea.org

A. Wahbi et al., *Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent*, https://doi.org/10.1007/978-3-319-69539-6_4

9]. Note that the biomass signal is fairly small and challenging to remove from the soil moisture signal and inherent noise in the neutron counts. This requires use of large detectors (i.e., high count rates on the order of 5000 to 10,000 to minimize uncertainty) and certain biomass detection limits (i.e., on the order of 0.5 kg/m^2). Nevertheless the technique is theoretically sound [6] and an area of active research.

4.2 Relationship Between Neutrons and Crop Biomass

During the CRNS calibration process, the variable "N_0" is calculated for each field site in a particular experiment. N_0 is a theoretical count rate of neutrons detected by the CRNS in an environment devoid of vegetation with dry silica soils present within the instrument footprint. The role of this variable in the calibration function is given by Desilets et al. [1]. Hawdon et al. [8] postulated on the use of the CRNS as a tool for the spatial mapping of biomass rather than soil moisture. The authors explain that once all sources of environmental hydrogen have been taken into account, the N_0 should be the same when calculated for all study areas. However, they had not yet taken into account the effect of growing maize biomass. As such, the authors determined in their study that ~ 80% of the variation in N_0 they observed was due to this biomass after all other sources of hydrogen had been quantified. Noted that for short grasslands, cereal crops, and legume crops with BWE changes of <2 kg/m^2 that N_0 will not be greatly affected. For use in maize, sugarcane, bamboo, and soybean, N_0 should be corrected for changes in BWE.

Franz et al. [4] determined a linear relationship between biomass water equivalent (BWE) and N_0 using a mobile CRNS within agricultural maize fields in central Nebraska, USA. Franz et al. [4] found a 1% decline in N_0 for every 1 kg/m^2 of BWE (R^2 of 0.51). In addition to this, Baatz et al. [9] demonstrated a similar relationship (i.e., 1% drop in N_0 for 1 kg/m^2 of biomass) between aboveground biomass and the CRNS counting rate N_0.

The procedures involved with determining aboveground crop biomass via the CRNS alone would involve predetermined experiments similar to those discussed previously. To be more specific, datasets would have to be made at specific study sites for any particular research project, between the CRNS N_0 counting rate and biomass water equivalent as determined via destructive sampling or remote sensing, and calculated via Eq. 2.1. Once multiple datasets have been made, a statistical relationship can be determined between the two variables; N_0 can be used as a predictive variable for aboveground crop biomass (assuming different study sites have similar crops and other environmental characteristics).

4.3 Direct Relationship Between Neutrons and Biomass

Preliminary theoretical and experimental work using multiple detector energies (bare, cadmium-shielded, and plastic-shielded detectors [10, 11]) is encouraging for detecting and separating multiple hydrogen signals, like soil moisture and biomass. Typically,

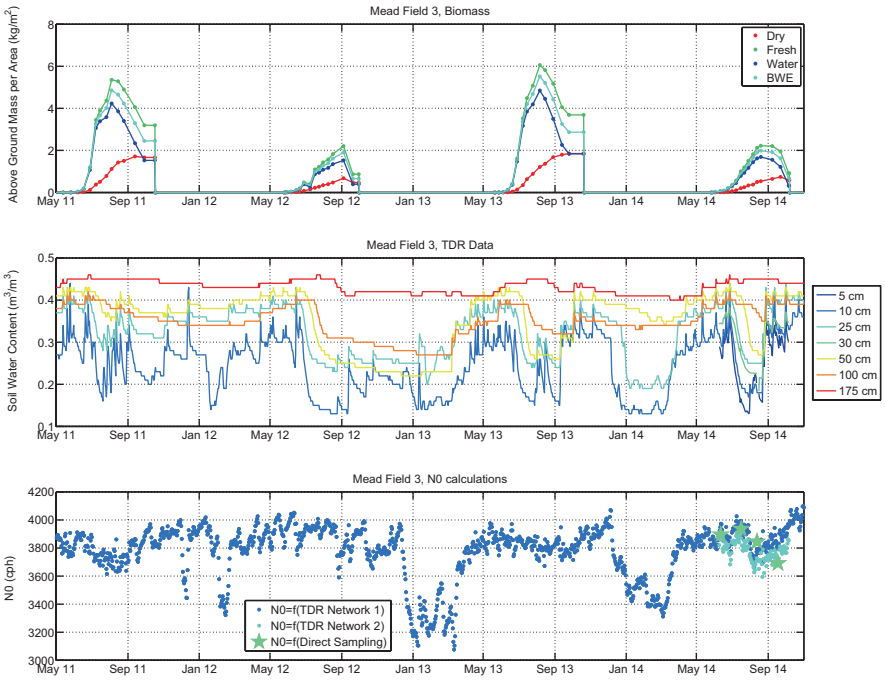


Fig. 4.1 (Top) Time series of daily dry, fresh, water, and biomass water equivalent biomass for a rotational maize and soybean field in Eastern Nebraska, USA [5]. Point values indicate direct sample collection dates. A linear interpolation (line) was used to create a daily dataset. (Middle) time series of spatially averaged TDR values from network 1 (5 locations) and network 2 (4 locations) for various depths. (Bottom) time series of daily N_0 values calculated from TDR network 1, TDR network 2, and direct sampling in 2014 using soil water content data between 0 and 30 cm (see [4] for details). Note that the ground may be covered in snow between December and March at the study site

most CRNS study sites have included a bare and plastic-shielded detector by default. The ratio of bare counts to plastic-shielded counts (aka thermal to fast ratio) has been shown to be correlated to direct estimates of BWE for a particular site [12].

Unpublished work by Franz shows promising results from Nebraska for maize and soybeans using relationships between N_0/BWE vs. bare to plastic count ratio vs. plastic count ratio. Figure 4.1 illustrates a daily time series of aboveground biomass, a soil water content monitoring network (TDR), and derived N_0 values. It is clear that having soil water content monitoring in the near surface (~5 cm depth) or direct sampling improves the relationship. Figure 4.2 illustrates the relationship between N_0, moderated counts, and bare to moderated ratio. Figure 4.3 illustrates the relationship between BWE, moderated counts, and bare to moderated ratio. Again a linear (i.e., a plane) relationship manifests in the data. This indicates that combining repeat-destructive sampling of BWE over the course of a growing season with bare and moderated neutron counts can be used to directly estimate BWE changes through time. An appropriate suggestion is that a minimum of 5–7 destructive sampling periods are used to estimate the coefficients describing the equation of a plane:

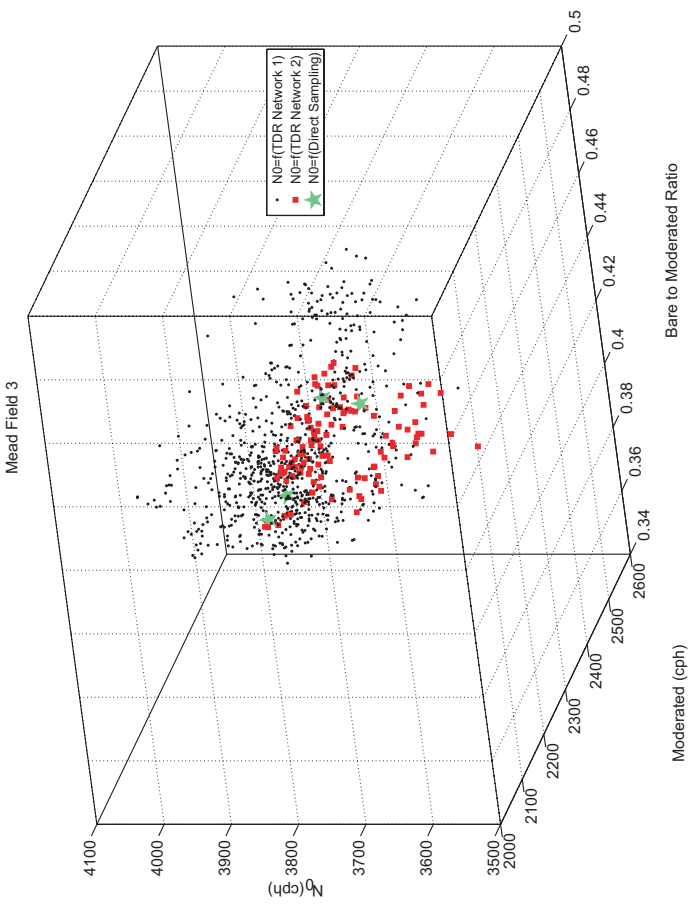


Fig. 4.2 Illustration of relationship between computed N_0 vs. moderated vs. bare to moderated ratio for TDR network 1 (R^2 = 0.440, RMSE = 65.13 cph, N = 832), TDR network 2 (R^2 = 0.611, RMSE = 42.62 cph, N = 117), and direct sampling in 2014 (R^2 = 0.883, RMSE = 36.64 cph, N = 4). Note only data from April 1 to October 31 is used to remove snow effects

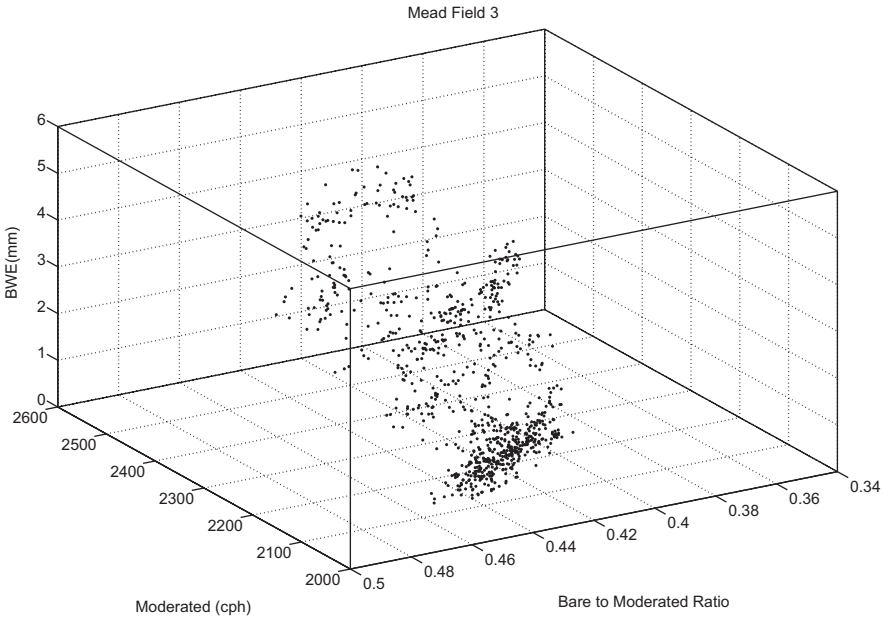


Fig. 4.3 Relationship between observed daily average moderated neutron counts, bare to moderated ratio, and BWE. Regression indicates a plane fits the data well ($R^2 = 0.8476$, RMSE = 0.631 kg/m^2, N = 832). The relationship to biomass appears to be linear for soybean and corn with BWE less than 6 kg/m^2

$$BWE = a + b^* M + c^* BM \tag{4.1}$$

where a, b, and c are locally defined coefficients, M is corrected moderated neutron counts, and BM is the ratio of raw bare and moderated neutron counts (no corrections are needed for the ratio). Note that the signal to noise ratio is small and suggests high count rates be used for M and BM (> 20,000). This can be achieved by using daily to multiday averages or multiple detectors. Note that given the dependence of detected plastic-shielded neutrons and bare neutrons (i.e., thermal neutrons are generated from local fast neutrons), local factors may affect this relationship. Figures 4.4 and 4.5 illustrate the derived daily BWE for rainfed maize in 2011 and rainfed soybean in 2014. Note that the derived BWE is very similar in shape (unscaled) to seasonal crop coefficient (kc) relationships [13] widely used in agricultural practice. Accurate determination of daily crop coefficient has large potential practical use in irrigation scheduling and calibration and validation of remote sensing products. The combination of an accurate soil moisture and crop coefficient makes CRNS an exciting tool to combine with crop simulation models like FAO AquaCrop, for real-time applications of water management and yield forecast. Lastly, note that techniques of energy separation using a third cadmium-shielded detector may be necessary, in addition to quantifying the differences in background hydrogen (i.e., lattice water) that may affect the a, b, and c coefficients in Eq. 4.1. The area of multi-signal hydrogen separation using CRNS remains an exciting and challenging research area.

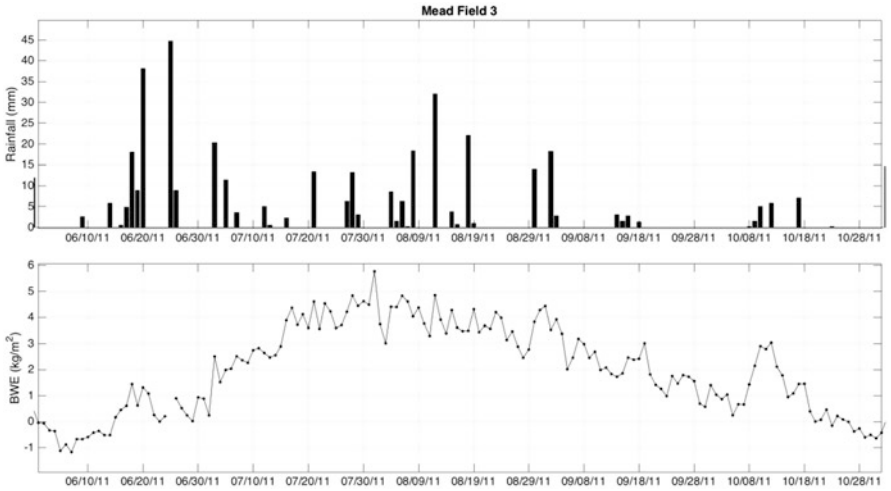


Fig. 4.4 Derived daily BWE for rainfed maize in Eastern Nebraska in 2011. Note the shape of BWE over the growing season is very similar to crop coefficients (scale from ~0 to 1) widely used in agricultural practice

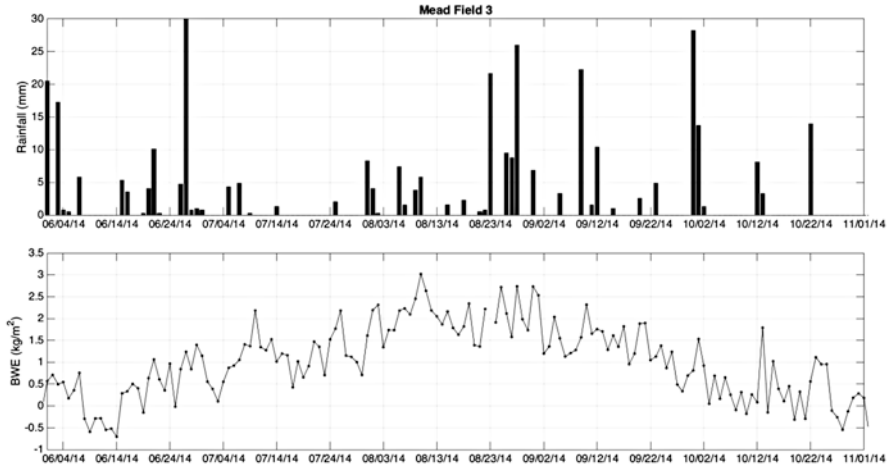


Fig. 4.5 Derived daily BWE for rainfed soybean in Eastern Nebraska in 2014. Note the shape of BWE over the growing season is very similar to crop coefficients (scale from ~0 to 1)

4.4 Conclusions

The presence of agricultural biomass within the footprint of the CRNS contributes its hydrogen to the signal of the sensor. As such, a calibration aimed in part to quantify the hydrogen in said biomass as a function of its water equivalent (BWE, Eq. 2.1) is employed. It is possible with sufficient comparisons of the CRNS counting

rate "N_0" and BWE for the CRNS to be used as a tool for mapping biomass within agricultural environments. Preliminary and theoretical works indicate an opportunity for multi-detector CRNS to separate and isolate multiple hydrogen sources simultaneously. Furthermore, note that the derived BWE is very similar in shape (unscaled) to seasonal crop coefficient relationships widely used in agricultural practice. This has large potential practical uses in irrigation scheduling, calibration and validation of remote sensing products, and use in simulation models like FAO AquaCrop. It is important to consider this application due to the inherent advantages the CRNS possesses in regard to mapping spatial soil moisture, in particular its large spatial footprint and noninvasive and nondestructive nature.

This publication illustrates three techniques for the estimation of crop biomass for use in the CRNS calibration function: destructive in situ sampling, remote sensing of the land surface via satellites, and the sensing of biomass via the CRNS itself. These three methods give environmental scientists additional tools for investigations into agricultural ecosystems and human use of the land and water. Ultimately, this work is intended to serve as a supplemental guideline for the use of the CRNS around the world.

References

1. Desilets D, Zreda M, Ferre TPA (2010) Nature's neutron probe: land surface hydrology at an elusive scale with cosmic rays. Water Resour Res 56:W11505
2. Zreda M, Schuttleworth WJ, Zeng X, Zweck C, Desilets D, Franz T, Rosolem R (2012) COSMOS: the cosmic ray soil moisture observing system. Hydrol Earth Syst Sci 16:4079
3. Franz TE, Zreda M, Ferre PA, Rosolem R, Zweck C, Stillman S, Zeng X, Shutt WJ (2012) Measurement depth of the cosmic ray soil moisture probe affected by hydrogen from various sources. Water Resour Res 48:W08515
4. Franz TE, Wang T, Avery W, Finkenbiner C, Brocca L (2015) Combined analysis of soil moisture measurements from roving and fixed cosmic ray neutron probes for multiscale real-time monitoring. Geophys Res Lett 42:3389
5. Avery WA, Finkenbiner C, Franz TE, Wang T, Nguy-Robertson AL, Suyker A, Arkebauer T, Munoz-Arriola F (2016) Incorporation of globally available datasets into the roving cosmic ray neutron probe method for estimating field-scale soil water content. Hydrol Earth Syst Sci 20:3859
6. Franz TE, Zreda M, Rosolem R, Hornbuckle BK, Irvin SL, Adams H, Kolb TE, Zweck C, Shuttleworth WJ (2013) Ecosystem scale measurements of biomass water using cosmic ray neutrons. Geophys Res Lett 40:3923
7. McJannet D, Franz TE, Hawdon A, Boadle D, Baker B, Almeida A, Silberstein R, Lambert T, Desilets D (2014) Field testing of the universal calibration function for determination of soil moisture with cosmic ray neutrons. Water Resour Res 50:5235
8. Hawdon A, McJannet D, Wallace J (2014) Calibration and correction procedures for cosmic ray neutron soil moisture probes located across Australia. Water Resour Res 50:5029
9. Baatz R, Bogena HR, Hendricks Franssen J, Huisman A, Montzka C, Vereecken H (2015) An empirical vegetation correction for soil water content quantification using cosmic ray probes. Water Resour Res 51:2030
10. Andreasen M, Jensen KH, Zreda M, Desilets D, Bogena H, Looms MC (2016) Modeling cosmic ray neutron field measurements. Water Resour Res 52:6451

11. Andreasen M, Jensen KH, Desilets D, Zreda M, Bogena HR, Looms MC (2017) Cosmic-ray neutron transport at a forest field site: the sensitivity to various environmental conditions with focus on biomass and canopy interception. Hydrol Earth Syst Sci 21:1875
12. Tian ZC, Li ZZ, Liu G, LI BG, Ren TS (2016) Soil water content determination with cosmic-ray neutron sensor: correcting aboveground hydrogen effects with thermal/fast neutron ratio. J Hydrol 540:923
13. Allen RG, Pereira LS, Raes D, Smith M (1998) Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements, FAO Irrigation and Drainage Paper 56. Food and Agriculture Organization of the United Nations, Rome

Contributors to Drafting and Review

Avery, W.	International Atomic Energy Agency
Dercon, G.	International Atomic Energy Agency
Franz, T.	University of Nebraska-Lincoln, United States of America
Heng, L.	International Atomic Energy Agency
Oismueller, M.	Vienna University of Technology, Austria
Strauss, P.	Federal Agency for Water Management, Austria
Wahbi, A.	International Atomic Energy Agency

A. Wahbi et al., *Cosmic Ray Neutron Sensing: Estimation of Agricultural Crop Biomass Water Equivalent*, https://doi.org/10.1007/978-3-319-69539-6