Ecosystem Services Provided by Agricultural Land as Modeled by Broad Scale Geospatial Analysis

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Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy
In
Geospatial and Environmental Analysis

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February 17, 2014
Blacksburg, VA

Keywords: GIS, Remote Sensing, Agriculture, CDL, VALUES, RYE, Ecosystem Services

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ABSTRACT

Agricultural ecosystems provide multiple services including food and fiber provision, nutrient cycling, soil retention and water regulation. Objectives of the study were to identify and quantify a selection of ecosystem services provided by agricultural land, using existing geospatial tools and preferably free and open source data, such as the Virginia Land Use Evaluation System (VALUES), the North Carolina Realistic Yield Expectations (RYE) database, and the land cover datasets NLCD and CDL. Furthermore I sought to model tradeoffs between provisioning and other services. First I assessed the accuracy of agricultural land in NLCD and CDL over a four county area in eastern Virginia using cadastral parcels. I uncovered issues concerning the definition of agricultural land. The area and location of agriculture saw little change in the 19 years studied. Furthermore all datasets have significant errors of omission (11.3 to 95.1%) and commission (0 to 71.3%). Location of agriculture was used with spatial crop yield databases I created and combined with models I adapted to calculate baseline values for plant biomass, nutrient composition and requirements, land suitability for and potential production of biofuels and the economic impact of agriculture for the four counties. The study area was then broadened to cover 97 counties in eastern Virginia and North Carolina, investigating the potential for increased regional grain production through intensification and extensification of agriculture. Predicted yield from geospatial crop models was compared with produced yield from the NASS Survey of Agriculture. Area of most crops in CDL was similar to that in the Survey of Agriculture, but a yield gap is present for most years, partially due to weather, thus indicating potential for yield increase through intensification. Using simple criteria I quantified the potential to extend agriculture in high yield land in other uses and modeled the changes in erosion and runoff should conversion take place. While the quantity of wheat produced though extensification is equal to 4.2 times 2012 production, conversion will lead to large increases in runoff (4.1 to 39.4%) and erosion (6 times). This study advances the state of geospatial tools for quantification of ecosystem services.

Acknowledgements

Conducting a dissertation is a long and grueling process like running the Marathon. In January 2010 when I commenced I found myself at the start, at the Tomb of the Marathon Warriors, submitting the ETD is like entering the Panathenaic Stadium, I will cross the finish line when graduate school approves it. I feel the need to thank the people that have kept me on the path and helped me continue running. First I want to thank my committee members, my advisor Dr Hodges for the support, funding and advice he has given me, Dr Campbell for helping me keep the formalities of the GEA program, Dr Kim for giving me his outsider view and showing me the milestones I need to pass, which when running the race I easily miss and Dr Wynne, for finding the time to tell me what works and what doesn't. Unlike the Marathon there is no blue line showing you the path to follow during the dissertation, my committee has been my blue line. There have been other members of the faculty which have assisted me in this dissertation, Drs Yang Shao, Valerie Thomas, Steven Prisley, Bill Carstensen, Kevin McGuire, John Galbraith, Lee Daniels and Wade Thomasson come to mind but I am certain that there are others that I have forgotten.

I wish to thank the other runners in my Marathon, my fellow Remote Sensing and Agronomy students. It is from my peers that I have been taught valuable lessons during classes and projects. I first wish to thank the people with which I have shared an office, Dong Yang, Jaixun Chai, Kiran Pavuluri and Ryan Stewart, your camaraderie has been invaluable. I wish to thank Beth Stein and her parents for their hospitality, her fellow foresters Kemal Gokkaya, Evan Brooks, Won Hoi Hwang, Ranjith Golapakrishnan, Laura Lorentz, Valquiria Quirino, Katie Correll, Adam Oliphant and anyone else I have forgotten. From Geography I wish to thank Tammy Parece, Baojuan Zheng, Taylor Seigler, Catherine Howey and anyone else I have forgotten. In classes, homework, field trips and projects you were there, with ideas on how to proceed on the problems. I must not forget though my fellow CSES students, Margaret Smith and Emily Sorensen, with whom I shared an advisor.

This dissertation would have been impossible without the help of several staff members, the people manning the refreshment stations for the runners along Marathonos, Messogeion and Vasilissis Sophias avenues. Without Pat Donovan this dissertation would have been impossible, she knew where to find the data and the tools necessary to finish my work. I wish to thank Les Fuller, Ted Elmore, the secretaries at Geography Karen Bland, Forestry Sue Snow and all secretaries at CSES, plus everyone I might have forgotten. I also wish to thank a few people I did not meet but provided me with data necessary to finish such as Anne Darby.

Graduation would be impossible without my friends, the people standing on the sidelines cheering the Marathon runners, giving them the courage to finish. I wish to thank my family members who have assisted me, my parents, my sister Arghyro and my first cousin Yiannis. My fellow Geography graduate students who showed up at Happy Hour, Brent Sams and his charming wife Lauren, Jason McVay, Andrew Evans, Arvindh Bhuta and his charming wife Candace, Rachael Lubbitz and all that crowd that has mostly graduated and thus their name (but not their face or their company) slips from my mind. From CSES I want to thank Stephanie Kulesza, Rob Norris, Terry Sosienski, Alicia Hunolt whose name I always forget, and everyone else who shows up and talks to me, despite my demeanor. I wish to further thank my friends at OCF and VTLUUG for the wonderful time we have spent together.

However it has been with the other Greek students that I have had the most cultural affinity and have spent the most time together. Without you to take me out at night so we can release our frustration, pain and struggles with our dissertation and general life in Blacksburg as song and dance on the dancefloor, I would have never graduated. Fotini Vassilikou and Eirini Asprouda were invaluable in the first years, Konstantinos Krommydas and Michalis Michaelides more recently. I will not list you all, I will thank in person during the Easter celebration but I need to give a special mention here to Nikos Artavanis but also Alan Moore and David Kramar, when in June 2010 I was as stranded as the Ten Thousand after the Battle of Kunaxa, you and Dr Prisley gave me shelter and the courage to continue and march like the Ten Thousand towards home and my finish line.

Preface and Attribution

This document is organized into five parts with an Introduction, three manuscripts composing the body of the work and conclusions. The first manuscript is organized as a submission for Photogrammetric Engineering and Remote Sensing (PE&RS). The second manuscript has already been published at the Proceedings of the Second International Conference in Agro-Geoinformatics and is copyright 2013 IEEE. The third manuscript is in preparation for eventual publication in an appropriate journal. The chapters were all collaborative efforts involving mainly the work of the author with significant guidance and editing of the committee members.

More specifically the first manuscript, "Positional Validation of Agriculture in Land Cover Layers in Select Virginia Counties" is in preparation to be submitted to PE&RS. Principal author is Ioannis Kokkinidis who performed the data analysis and preparation of the manuscript. Coauthors are Dr. Steven Hodges and Dr. Randy Wynne who provided editing, textual analysis and scientific guidance in preparation of the paper. Furthermore it has benefited from the insight of a variety of other members of the academic community at Virginia Tech such as Dr. James Campbell, Dr. Mintai Kim, Dr. Yang Shao and the students of NR 6104 who have read and commented on the manuscript and the methods during various stages of preparation.

The second manuscript "Calculating Ecosystem Services provided by agricultural land using GIS and Remote Sensing methods" was coauthored by Ioannis Kokkinidis and Steven Hodges and is published in the Proceedings of the Second International Conference in Agro-Geoinformatics, p. 164-169, a publication of IEEE Journal of Selected Topics in Applied earth observations and Remote Sensing (IEEE JSTARS). The article has a DOI: 10.1109/Argo-Geoinformatics.2013.6621901 and is available online at http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6621901. Ioannis Kokkinidis performed data analysis and manuscript preparation Dr. Steven Hodges provided editing, textual analysis and scientific guidance in preparation of the paper.

The third manuscript "Identifying productive gaps and selecting area appropriate for conversion to small grain production in eastern Virginia and North Carolina" was coauthored by Ioannis Kokkinidis and Steven Hodges and will be published in an appropriate agriculture and GIS modeling journal. Data analysis and preparation of the manuscript was performed by Ioannis Kokkinidis. Patricia Donovan transformed VALUES from the Excel format where Ioannis Kokkinidis had left it into an MS Access Database. Dr. Steven Hodges provided editing, textual analysis and scientific guidance in preparation of the paper, while the committee members provided their comments in preparation for this ETD.

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Introduction

Ecosystem Services

The notion of ecosystem services dates at least to the time of Plato who notes that deforestation reduced soil fertility and thus the capacity to grow food (Critias 111b- 111c). Modern studies began with Marsh (1864), who challenged the notion that Earth's resources are unlimited. More recently there have been several studies in the literature trying to properly define the concept of ecosystem services. De Groot et al (2002) wrote a seminal paper that attempted to standardize the framework for comprehensive assessment of ecosystem services. The Millennium Ecosystem Assessment report (MEA 2005) gave the following definition:

> Ecosystem services are benefits people obtain from the ecosystem

They subsequently divided ecosystem services into four categories and provided several examples (Table 1).

Type of Service	Examples
Supporting	Nutrient dispersal and cycling Seed dispersal Primary production
Provisioning	Food (including seafood and game), crops, wild foods, and spices Water Minerals (including diatomite) Pharmaceuticals, biochemicals, and industrial products Energy (hydropower, biomass fuels)
Regulating	Carbon sequestration and climate regulation Waste decomposition and detoxification Purification of water and air Crop pollination Pest and disease control
Cultural	Cultural, intellectual (educational) and spiritual inspiration Recreational experiences (including ecotourism) Scientific discovery

Table 1. Partial list of ecosystem services

The MEA definition has been critiqued in that it includes both processes and final services that are provided by ecosystems (Wallace 2007). While it has not gained universal acceptance at least yet[1], it is by far the most frequently referenced definition used. I used this definition and its framework to investigate the ecosystem services provided by agricultural land in my study area and to create and evaluate methods to quantify their flows and values.

[1] Wallace (2007) noted that it also took several decades of debate before settling the question of what to include in the Gross Domestic and Gross National Products.

Ecosystem services and agricultural land

As I discovered early in the course of my dissertation there is no generally accepted definition of “agricultural land”. The obvious definition is that agricultural land is the land where agriculture takes place, but agriculture itself is a process that is very diverse, has strong spatial heterogeneity depending on where it is practiced, can range from the sole activity practiced in one location to a minor component of land use in another, thus making it challenging to specifically associate certain types of land with agriculture. Furthermore remote sensing studies tend to show that it is more of a socially defined practice rather than a spectrally defined category (Kokkinidis 2007). The United States Department of Agriculture (USDA) also does not have a definition of ‘agricultural land’ specific to the United States. The European Union defines it as follows (GEMET Thesaurus 2014):

> Agricultural land is land used primarily for the production of plant or animal crops, including arable agriculture, dairying, pasturage, apiaries, horticulture, floriculture, viticulture, animal husbandry and the necessary lands and structures needed for packing, processing, treating, or storing the produce.

Agricultural land provides a large number of benefits. Protecting farmland is good land planning since it maintains open space, preserves rural lifestyles, prevents urban sprawl, controls infrastructure costs and preserves the local economy. It provides environmental protection by protecting watersheds, maintaining air quality, retaining natural systems and resources. Also through food and fiber production we maintain agricultural production capacity, promote local self-sufficiency and maintain specialty crops (Heimlich et al 1991).

As the MEA framework emphasizes, the economic and social benefits of the food and fiber system are not limited just to food and fiber. As Lipton et al noted (1998) they require the input of seeds, fertilizers, pesticides, farm equipment and financial services. In turn this stimulates manufacturing, mining and the transportation sector. The value chain tied to farm and fiber production includes farm elevators, food packers, food and textile mills, canneries, food processors, the paper industry, the alcohol industry and the energy sector.

While there are many studies and models on how the growth of urban areas or deforestation affect farmland, I could not find studies that used geospatial methods dealing primarily with the evolution and spatial distribution of agricultural land. Deforestation studies often imply that agricultural expansion is a process that must be stopped or reversed so as to protect the benefits provided by natural systems. Urban development studies have a tendency to treat farmland as undeveloped land rather than an economic and ecological asset in its own right.

Most complete among model collections to measure ecosystem services is the Integrated Valuation of Environmental Services and Tradeoffs (InVEST) suite. InVEST is an open source collection of tools created by the Natural Capitals project, housed at Stanford University. It is an attempt to quantify a variety of ecosystem services provided by multiple ecosystems, terrestrial, freshwater and aquatic (Tallis et al 2013). Its intention is to help inform stakeholders about the tradeoffs regarding various decisions that modify the landscape, using models that incorporate the best available scientific knowledge about a subject. It is available both as a standalone tool and as toolbox for ArcGIS. There has been a variety of publications based on InVEST tools, a list of which is maintained at the Natural Capitals Project website.

There have also been a small number of papers that provide quantitative estimates of ecosystem services independently of InVEST. Costanza et al (2006) presented a comprehensive synthesis report giving monetary value to ecosystem services produced in the whole state of New Jersey. Applying the results of 100 previous studies, they calculated that the value of ecosystem services for 2005 was between $11 and $19 billion. Pasture/Grassland provided ecosystem services worth $6,751,242 – $44,623,493 while cropland provided $2,103,089 - $78,302,761 worth of ecosystem services. The large valuation difference is due to the use of studies of questionable quality to calculate some of the value for ecosystem services. These numbers do not include the value of food produced in these lands. Furthermore using the values for ecosystem services they attempted to calculate the value of Natural Capital but due to lack of well accepted discount values they could only give rough estimates.

Raudsepp-Hearne et al (2010) modelled the spatial patterns of 12 ecosystem services in 137 municipalities of Quebec. They identified six types of ecosystem service bundles and that they were able to link these bundles to areas on the landscape characterized by distinct social–ecological dynamics. Optimizing provisioning ecosystem services tended to reduce most regulating and cultural services.

Objectives

Principal objectives of this dissertation were to explore and quantify the variety of ecosystem services provided by agricultural land using Geographic Information Systems and Remote Sensing. I hoped to move the conversation on ecosystem services provided by agricultural land from a qualitative discussion on the scope of ecosystem services into a quantification of actual values of ecosystem services. My hypothesis was that GIS and Remote Sensing can be used to provide realistic quantitative estimates of ecosystem services provided by agricultural land. The main method used in the dissertation was the adaptation of quantitative models that described specific ecosystem services and use of the models to generate numeric values for the specific locations studied. I also attempted to validate such models whenever relevant data was accessible, and thus evaluate their realism and utility. The breadth of ecosystem services provided by agricultural land that I investigated was not exhaustive and was determined by the availability of existing models and data. More specifically the objectives pursued in this dissertation were:

- Create spatial realistic yield maps based on soil maps and realistic yield tables
- Evaluate the quality of agricultural land layers of the available land cover land use products
- Evaluate the suitability of land for agriculture, including biofuel production, based on objective criteria
- Create a model to calculate full plant biomass, above and belowground, based on yield
- Calculate elemental composition of important nutrients in biomass in a spatial context
- Calculate a realistic estimate of economic output that can be used to compare quantitative values of ecosystem services
- Evaluate the potential for intensification of crop production in current agricultural land

- Generate a realistic estimate of the land suitable for conversion to agriculture and realistic production estimate for crops grown in such land
- Create spatial models of erosion and runoff

Overview

I purposely limited myself whenever possible to data that was available broadly and freely, preferably open source and public domain data, so that my methodology could be replicated by future researchers for other locations. Principal dataset used was the Virginia Agronomic Land Use Evaluation System (VALUES) and, to a lesser extent, its North Carolina equivalent the Realistic Yield Expectations (RYE) database. Furthermore I used the Soil Survey Geographic Database (SSURGO), the National Land Cover Dataset (NLCD), the National Agricultural Statistical Service's (NASS) Cropland Data Layer (CDL), the Economic Research Service's (ERS) Quickstats statistical database of farm data, the National Resource Conservation Service's (NRCS) Crop Nutrient Tool, the ERS Fertilizer and Price Database, Virginia Cooperative Extension's farm budgets, Oregon State University's PRISM climate group climatic data and several other open datasets to a lesser extent. Among the less available data I used cadastral parcel information for four Virginia counties.

The core of my dissertation was the database join between SSURGO, in either vector or raster format (gridded SSURGO) with soil yield databases (VALUES and RYE). The result of this is a series of spatial realistic yield database for major crops in the area to which the joined SSURGO dataset refers. These crop yield layers are both main products and joining threads of my dissertation; they open new possibilities for analysis of agriculture and its practices. I seek to evaluate the utility, accuracy and what is revealed about agriculture in Virginia and, eventually, North Carolina by the crop yield layers. To predict crop production for any plot of land I need to specify spatial location of the crop we seek to study, intersect or multiply this layer with the yield layer and sum the predicted production values derived from this new dataset. If we know the location of each crop grown, say from existing land cover layers, we can predict what a realistic yield should be. However this raises the question of the quality of land cover datasets available, which need to be validated. After producing an accurate land cover dataset and yield data, I can use ratios routinely used in crop breeding and the multiple tools created by USDA agencies to calculate plant living biomass and its elemental composition and estimate a variety of ecosystem services provided by agricultural land. Finally I can use land cover datasets to evaluate how current agricultural practices, as shown in national statistics, compare to what is predicted by VALUES and RYE. I evaluate the potential to convert other land uses into agricultural land and model potential changes to runoff and erosion should this conversion take place.

Before blindly accepting the outputs of land cover layers, particularly in this mixed land use system where agriculture is frequently a minority to rare cover, and where no existing quality analysis exists, I wished to evaluate the uncertainty associated with the land cover layers. The first manuscript is thus a validation of land cover datasets available for Virginia. More specifically it evaluates NLCD 1992-2001 retrofit change detection layer and NLCD 2006, NASS CDL 2002, 2008, 2009, 2010 and 2011 for agricultural land of four selected Virginia counties: Albemarle, Charles City County, Chesterfield and Henrico. I discovered that there is no generally accepted US definition of agricultural land, and thus I used the European definition. I uncovered that there had been very little change in the extent of agricultural land over these years and most differences in agricultural land extent shown by the datasets were due to differences arising during the creation of said datasets. I used cadastral parcels to stabilize farm plots and performed visual interpretation of the land cover layers using National Agricultural Imagery Program orthophotoimagery. I found that specific accuracy varied according to the dataset and the validation method with an improvement across time of the dataset quality. Generally although area of the agricultural land cover layer was similar to what was actually agricultural land on the ground for most datasets, there were significant errors of omission and commission, a finding consistent with previous literature. We can generally trust the existing land cover layers, but with reservations.

In the second manuscript, published as a paper of the conference proceedings of the Second International Conference in Agro-Geoinformatics, I worked in the same four counties, using the validated land cover map to calculate numeric values for several Ecosystem Services provided by agricultural land. Joining vector VALUES with SSURGO I created yield maps and then evaluated suitability of agricultural land for biofuel production. Using predicted yields I calculated total biomass and its associated nutrient composition, thus quantifying nutrient cycling and carbon fixation provided by agriculture. Carbon fixation was compared to what would be sequestered by a forest in the same land. VALUES production figures and validated area were compared with those from Quickstats for validation purposes, whenever the last were available[2]. Using the farm budget from Virginia Cooperative Extension I also calculated the economic output of agriculture. This resulted indicator of economic sustainability for comparison with quantitative estimated of ecosystem services provided by agricultural.

Finally on the third manuscript I expand the study area to cover the majority of agricultural land in Virginia, and North Carolina that is proximate to existing feed mills, primary users of grain in the two states. I used gridded SSURGO to rasterize VALUES and RYE into crop yield maps and intersected those with CDL 2008-2012 to calculate potential yield of cropland in the CDL. Area, production and yield figures were compared to those in Quickstats. Crop yield does not reach the yield goals given by VALUES and RYE most of the years, showing that there is significant potential for intensification of local agriculture. I also studied the potential for extensification of agriculture. I selected land having high potential production yield for wheat that was not currently in agriculture that could be converted to wheat production using several rational criteria. There is very high potential for conversion to agriculture in land currently in other uses. For Virginia land suitable for conversion is equal to 1.5 times the extent of 2012 agricultural land. For North Carolina it is equal to 25% of 2012 agricultural land. I attempt to consider tradeoffs between large increase in grain production and other ecosystem services by quantifying runoff and erosion before and after land conversion. For runoff I used two methods, Zhang's adaptation of Budyko's method (Zhang et al 2001), from the InVEST toolbox and Ferguson's (1996) extension of the SCS curve number method. For erosion I combined RUSLE 3d and the United Stream Power – based Erosion Deposition methods, both independently and in combination. The various methods agree that runoff and erosion would be increased in both states after conversion, though not to what degree.

[2] NASS does not release crop information for spatial units (counties, reporting districts, states) when less than 500 acres where grown of a particular crop or it was grown by a very small number of farmers

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Positional Validation of Agriculture in Land Cover Layers of Select Virginia Counties

The extent and location of agricultural land of Albemarle, Charles City, Chesterfield and Henrico counties of Virginia in NLCD 1992, 2001, 2006 and NASS CDL 2002, 2008, 2009, 2010, 2011 is not very accurate.

Abstract

NLCD and NASS CDL are freely available high resolution land cover datasets but their accuracy varies widely and is untested for agricultural land in Virginia. We performed validation through aerial photointerpretation of agriculture at the field level, using cadastral parcels as proxies for fields, over Albemarle, Charles City, Chesterfield and Henrico counties for NLCD 1992, 2001, 2006 and CDL 2002, 2008, 2009, 2010 and 2011. Different validation methods gave different measures of accuracy; errors of omission ranged 11.3-95.1%, errors of commission 0-71.3%. Extent of agricultural land in our validation layer differed from the Census of Agriculture. There was limited change in the extent of agriculture on the ground in the 19 year study period; comparison of layer pairs mostly reveals classification artifacts rather than change. The limited extent of agriculture and mixed land cover characteristics of the region suggest the use of multitemporal data to extract agricultural land cover

Introduction

In this study we investigate accuracies of major and often used land cover products applied to describe the locations and distributions of agricultural land in four counties in eastern Virginia. Knowing the distribution and extent of the different land covers is a necessity for climate modeling (Wilson and Henderson-Sellers 1985), natural resource inventory (Anderson et al 1976), spatial modeling (Pontius and Schneider 2001), land use land cover change detection (Lambin 1997) and multiple other purposes. Quantified data on the extent and location of agricultural land can be used as one of the inputs in models so as to quantify ecosystem services it provides including food and fiber provision (Santelmann et al 2004), primary production (Prince et al 2001), carbon fixation, nutrient cycling (Boody et al 2005), soil erosion and deposition (Wei et al 2008), water quality (Johnson et al 2012) and others and how change is affecting the ability of agroecosystems to provide its various benefits (Boody et al 2005). Since the outputs of models are dependent on their inputs, it is very important to understand the uncertainty associated with land cover datasets, especially in areas with diverse and heterogeneous landscapes.

There are few published studies dealing specifically with the quality of agricultural land cover layers at any spatial scale. These studies tend to focus on states (Johnson 2013), entire counties (Maxwell et al 2008, Goslee 2011) or at best arbitrary circular plots (Hollister et al 2004) as units of analysis. We assess the accuracy of the agricultural layer of several high resolution classifications over parts of the relatively humid and spatially heterogeneous Commonwealth of Virginia with the eventual aim of using them to track changes in the extent of agriculture. Our assessment is based on various validation methods: point to point validation, point to polygon and polygon to polygon using the cadastral parcels as the polygon unit of analysis. We test the hypothesis that cadastral parcels can be used as proxies for agricultural field as the unit of analysis so as to eventually allow agroecosystem services modelling with a high degree of precision. To the best of our knowledge the use of cadastral parcels as a unit to analyze land cover layers and assess their accuracy has not been attempted before and thus is a new methodology. For this reason we also evaluate the suitability of cadastral parcels in our study area for use as aggregation units, attempting to understand if it improves the ability to study farm fields or if it introduces little more than complexity and errors in the validation process. Finally we evaluate the evolution of agricultural land over time to track changes in its extent.

History and methods of validation

Before proposing a new validation methodology, it is important to see where it fits in the history and framework of validation. As Congalton and Green (2009) note, there are two types of accuracy, thematic and positional, which are interrelated. Foody (2002) identifies four developmental stages or “epochs" in the history of validation of remote sensing products, based on Congalton (1994). The first was the visual appraisal or “looks good” era, when makers of map products would just give a cursory glance to see if it looked proper. Next came the non-site specific map comparison era when percent accuracy between the dataset and a reference map was compared without taking into account specific overlap. The following epoch is the accuracy assessment stage, when class labels in the thematic map would be compared with a reference data for specific points. Finally we live in the era of the error matrix, introduced from the social sciences, which is a systematic evaluation of thematic labels with reference data. In the second epoch of validation comparison was between map extent of each class but without taking into account spatial overlap of the data and thus errors of omission and commission. In the third and fourth epochs, validation requires comparison of points on the layer with reference data points.

Study Area

We chose to examine four counties in eastern Virginia: Albemarle, Charles City, Chesterfield and Henrico (Figure 1). The adjacent independent cities of Charlottesville (Albemarle) and Richmond (Chesterfield and Henrico) are not included in our study. These counties offer a snapshot of the different socioeconomic processes affecting agricultural lands in the Commonwealth of Virginia. Albemarle

County still has a rural character but is undergoing rapid population growth and urbanization. Median farm size in 2007 was 32 hectares (80 acres) according to the 2007 Census of Agriculture (CoA) down from 38 hectares (93 acres) in 2002 (USDA 2009). By comparison the Virginia median was 29 ha (70 acres) in 2007, down from 32 ha (80 acres) in 2002 (USDA 2009). Chesterfield and Henrico Counties have had a suburban character throughout the 19 year period studied in this paper and their population has increased but at a slower pace than in Albemarle county (US Census Bureau 2013). Chesterfield is somewhat more urbanized and had a median farm size of 14 ha (35 acres) in 2007, down from 18 ha (44 acres) in 2002 (USDA 2009). Henrico also had a median farm size of 14 ha (35 acres) in 2007 but that was down from 19 ha (48 acres) in 2002 (USDA 2009). Charles City County is a very rural agricultural county that has not undergone significant land cover and population change over the 19 years studied. Median farm size in 2007 was 25 ha (63 acres), up from 24 ha (60 acres) in 2002 (USDA 2009).

Previous studies on the spatial extent of agricultural land in Virginia

Virginia, part of the Mid-Atlantic region, lies at the intersection of the urbanized Northeast and the more rural South. As such it displays characteristics that are relevant to a much broader region than just the state. Its population has been increasing (US Census Bureau 2014) resulting in conversion of different land covers into urban use. Furthermore, being in the humid East Coast of the United States, it has been difficult to spectrally differentiate agriculture from other vegetated classes. Very few remote sensing or land cover change studies have been performed on the general characteristics and extent of agriculture of Virginia. Hrezo (1980) used National Resources Inventory statistics to describe how development has replaced prime farmland in Virginia during the post-WWII period and outlined methods to combat this phenomenon, such as conservation easements. Gildea (2000) investigated the effect of land cover change on stream water quality in Virginia. He evaluated the Virginia Forest Inventory and Analysis, the Census of Agriculture, the National Resources Inventory, the USGS Land Use Land Cover (LULC) layer which dates and refers to the late 1970's-early 1980's and the National Land Cover Database (NLCD) for

1992. He found that the datasets had significant differences in land cover values, since each used unique land use classification definitions. For his comparison he used USGS LULC and NLCD 1992, whose classification schemes had to be reconciled to enable comparison, so as to quantify land cover change within watersheds in which he had collected water samples and measure its effect on water quality.

Data and Quality

Datasets used

There is a variety of land cover datasets available, regional and global, that cover the study area. We chose to work with the highest resolution datasets available which belong to two families: the National Land Cover Dataset (NLCD) and the Cropland Data Layer (CDL). The Multiresolution Land Consortium (MRLC), a consortium of various American Federal, State agencies and Research Institutions, has created a systematic classification of land cover of the entire United States in raster format that is known as the National Land Cover Database. It was created first for the year 1992 as a follow up to the 1970's-early 1980's USGS LULC. The original intention was to create a new NLCD every decade but after the 2001 dataset, MRLC reduced the return time to 5 years. It is based mostly on Landsat imagery; uses decision tree classification and has a spatial resolution of 30 meters. The classification scheme differs in all years but more significantly among NLCD 1992 with those that follow it. Hence a Retrofit Land Cover change product was created by Fry et al. (2009) to facilitate comparison between NLCD 1992 and 2001. For this study we used this 1992-2001 retrofit change detection layer, split into different datasets for 1992 and 2001, and the NLCD 2006 layer (Fry et al 2011). Minimum Mapping Unit (MMU) for both products is 5 pixels which corresponds to 0.45 ha.

The USDA's National Agricultural Statistical Service (NASS) has since the mid-1990’s created a land cover dataset with an agricultural emphasis that is called the Cropland Data Layer (CDL). It is produced on an annual basis. The first CDL in 1996 covered 3 counties of the Midwest, was produced for more regions each year and since 2008 has covered the conterminous United States. Special characteristic of this layer is that NASS uses the confidential farmer declarations to the Farm Services Administration (FSA) to create a ground truth sample for classification and validation (Johnson & Mueller 2010). For the Mid-Atlantic States, including Virginia, CDL was created for 2002 based on LANDSAT imagery by Towson University and NASS (Mueller 2005). CDL for Virginia next becomes available from 2008 on. Due to Landsat 9 Scan Line Correction failure they supplemented Landsat imagery with Resourcesat, Deimos 1, UK-DMC2 and MODIS imagery. For this study we used all available CDL layers between 2002 and 2011. CDL 2002, 2010 and 2011 have a 30 meter pixel while CDL 2008 and 2009 have a 56 meter pixel. CDL does not have any filtering or smoothing with the exception of the citrus category in Florida (Boryan et al 2011).

Accuracy assessment according to dataset producers

Accuracy assessment of NLCD 1992 was organized around the 10 EPA Federal districts which were also used in creating the dataset (Stehman et al. 2003). Each district was divided into framing cells from which an equal number of samples was originally selected, then a second sample was selected to cover rare land cover classes. The selected samples were compared with high resolution 1989-1993 aerial imagery. The sampling unit was a 3 x 3 pixel sampling window, with the majority class chosen in cases of heterogeneity. For the Mid-Atlantic Region Anderson level I accuracy was at 70±2.6% and level II accuracy was 43±3.9%.

For accuracy assessment purposes NLCD 2001 was also divided into 10 regions but they were different from those of NLCD 1992 (Wickham et al. 2010). They again picked random samples within framing cells but chose 100 samples from each class in each region, resulting in 15,000 samples across the country. Individual pixels were validated using photointerpretation of Digital Orthophoto Quarter Quads

(DOQQs). For Region 9 (East Coast except New England) Anderson level I accuracy was 81±1.5% and level II 71±1.8%. Accuracy assessment of NLCD 2006 has yet to be published.

NASS' special agreement with the FSA regarding the Cropland Data Layer allows the validation of the product based on georeferenced farmer declarations rather than photointerpretation. CDL, whose classification scheme is similar to Anderson level II, claims accuracy in the order of 85% for Virginia with higher accuracy for the major crops of each area. There is no reference dedicated to describing how validation took place but Johnson & Muller (2010) and Boryan et al (2011) describe the process. Before 2005 they would extract random points from digitized farm plot polygons produced each year through photointerpretation of high resolution area imagery. Farmer crop declarations to the FSA were associated with farm polygons and the sample was split 70:30 for classification and validation. Since 2005 it is Common Land Unit (CLU) polygons that are associated with the declarations. For non agricultural classes they use NLCD 2006 as the validation layer.

Independent validations

NLCD and CDL have seen a large number of applications in LULC studies. There have also been a few independent studies to evaluate the accuracy of their information that included validation of the agricultural layer. Among the studies Maxwell et al (2008) and Goslee (2011) belong to the second epoch of validation, Johnson (2013) belongs to the third and Hollister et al (2004) to the fourth.

Hollister et al (2004) validated NLCD 1992 over Rhode Island and Massachusetts through comparison to local land cover products for these states. The Massachusetts dataset is called MassGIS LULC and was created through photointerpretation of high resolution 1987-1995 aerial imagery. The Rhode Island product is called RIGIS LULC and was created through photointerpretation of 1995 DOQQs. They wished to test dataset accuracy for different scales and different classes. They created circular samples that had different radii so as to encompass areas from 0.1 to 200 km^2. Agriculture did not display significant differences in extent between NLCD and the state land cover layers, however there were significant errors of omission and commission that cancelled out. Also for areas less than 7 to 20 km^2 there were significant differences in the accuracy of the extent of the NLCD's land cover classes.

Maxwell et al (2008) compared the cropland layer of NLCD 2001 and CoA statistics of 2002 for 14 states in the Upper Midwest, also known as the Corn Belt. The unit of analysis was the county. The authors calculated how many hectares of cropland were in NLCD in each county and then compared this value with the figure given in the Census of Agriculture, which they considered to be the more accurate. The biggest differences among the datasets were found in counties that are along the edges of the study area and had the lowest proportions of cropland. There were also significant differences in areas where the landscape is dominated by cropland and forest complexes such as most of Wisconsin, and parts of the non-irrigated plains such as the Dakotas where NLCD was not able to differentiate well dry cereal crops from prairie grasses. Further potential causes for the discrepancies were, according to the authors, that the two datasets referred to different years and the smart eliminate algorithm applied to NLCD to smooth the data to a 0.4 ha MMU.

Goslee (2011) compared CoA 1992 with NLCD 1992 and CoA 2002 with NLCD 2001 for all agricultural classes for 12 states in the Northeast. Unit of analysis was again the county. She tested several agricultural land cover classes in each county that had equivalent in the CoA, interpolating where the latter did not offer data due to farmer confidentiality. There were differences between the datasets depending on the crop and the state. NLCD tended to overestimate agricultural grassland and underestimate cropland with these two errors cancelling out, resulting in good estimates of the extent of broader agriculture.

Johnson (2013) developed a circa 2010 map of annually tilled land of the conterminous United States, based on aggregation of CDLs from 2008 to 2011, and compared it to the 2007 CoA. His definition of annually tilled land includes field crops such as corn, wheat and soybean, non-tree fruit crops but not perennials such as pastures, vineyards and fruit trees. He found that compared to the 2007 CoA his layer systematically underestimated the extent of tilled land at the state level with the biggest discrepancies at Montana and North Dakota, where CDL has trouble differentiating unirrigated cereals from grass pasture. To compare with NLCD 2006 he added orchards to his tilled layer and found that it also systematically underestimated cropland, though to a much lesser extent than when comparing with the CoA. He also notes that even though the extents of the layers match quite well, pixel location does not. For all states 81.7% of all pixels matched as non-cultivated in both datasets, 12.7% matched as cultivated, 3.4% were cultivated in NLCD but not in CDL and 2.1% were cultivated in CDL but not in NLCD.

Data harmonization

Creating a uniform scheme

Harmonizing classifications to facilitate comparison among different land use land cover datasets is an open issue, even at the global level (Herold et al 2006). For the United States seminal was the work performed by Anderson et al (1976). While most datasets produced in the United States follow its general principals, very few follow it exactly to the word. NLCD and CDL are no exceptions, with each dataset using its own somewhat different scheme inspired by Anderson level II. Since they follow the same principles they can be harmonized into an Anderson level I scheme (Table 1), though for some years and classes no appropriate equivalencies were found. Since this paper deals with agriculture a more detailed discussion on what specific land covers should be included in the category “agricultural land” follows.

Defining agriculture

When defining which land covers to include in the “agricultural land” category for our validation study, it is critical to clearly lay out how we deal with range, grasslands, shrublands, and pasture land covers. For the purpose of evaluating ecosystem services, we placed pasture land covers (including hay lands) within the agricultural category. In the study area, pastures are typically managed with inputs of energy and materials to provide provisioning services. When Anderson et al (1976) define agricultural land at level I, they note:

> Agricultural land has been defined to include Cropland and Pasture; Orchards, Groves, Vineyards, Nurseries, and Ornamental Horticultural Areas; and Confined Feeding Operations as the principal components. Certain land uses such as pasture, however, cannot be separated consistently and accurately by using the remote sensor data sources appropriate to the more generalized levels of the classification. The totality of the category thus closely parallels the U.S. Department of Agriculture definition of agricultural land.

Hollister et al (2004), Maxwell et al (2008), Goslee (2011) and Johnson (2013) all demonstrated that it was difficult to differentiate between pasture/grassland and agriculture. Thus it is interesting to see what the definition that Anderson et al (1976) gave for Rangeland is:

> The principal concept by which certain types of cover are included in the Rangeland category, and which separates rangeland from pasture land, is that rangeland has a natural climax plant cover of native grasses, forbs, and shrubs which is potentiality useful as a grazing or forage resource. Although these rangelands usually are not seeded, fertilized, drained, irrigated, or cultivated, if the forage cover is improved, it is

> managed primarily like native vegetation, and the forage resource is regulated by varying the intensity and seasonality of grazing. Since the typical cropland practices mentioned just above are characteristics of some pasture lands, these pasture lands are similar in image signature to cropland types.

Anderson et al. (1976) thus define rangeland in opposition to agricultural land in that rangeland is in a somewhat natural state while agricultural pasture land is highly managed. In terms of ecosystem services we can think of the rangelands of our region as being less intensive pastures, offering a subset of provisioning services but more biodiversity services, falling within the broad spectrum of agricultural land. The classifications mentioned above and used for this study disagree on which category pastures belong. NASS considers pasture land to be agricultural land but is classified differently in CDL. In order to proceed with investigations a consistent definition of agricultural land is necessary. While Anderson mentions a USDA definition of agricultural land, there is no such definition in the National Agricultural Library (USDA NAL 2014). For that matter there is no generally accepted American scientific definition for it as far as we could find. Thus we have decided to use the European Environmental Agency definition of agricultural land for the English language (GEMET Thesaurus 2014):

> Agricultural land is land used primarily for the production of plant or animal crops, including arable agriculture, dairying, pasturage, apiaries, horticulture, floriculture, viticulture, animal husbandry and the necessary lands and structures needed for packing, processing, treating, or storing the produce.

According to this definition forests where apiculture takes place are agricultural lands, as is land taken by Concentrated Animal Feeding Operations or processing facilities. On the other hand golf courses, parks, stadiums and lawns are not agricultural lands. Pasture is defined by GEMET (Thesaurus, 2014) as "Land covered with grass or herbage and grazed by or suitable for grazing by livestock", thus it includes land considered rangeland by Anderson et al (1976). For our purposes we thus modify the Anderson definition of agricultural land so that for our use it includes row crops, pastures, rangeland and all other categories of land that support or are primarily intended to support agriculture. Furthermore we place emphasis on land cover rather than land use (see also the word "primarily" in the GEMET definition), if a field was left fallow in this study we consider it to be agricultural land. Table 2 is the lookup table for the agricultural land cover class used in this study, based on the definition of agricultural land used.

Ancillary data for validation

Aerial Imagery

For our purposes we performed photo interpretation of the agricultural land cover of the study area. To achieve this we used several georeferenced aerial images that were available at the USDA Geospatial Data Gateway taken as close as possible to the year the dataset refers to. More specifically we used 1995 DOQQs to validate NLCD 1992, National Agricultural Imagery Program (NAIP) images from 2003 for NLCD 2001 and CDL 2002, NAIP imagery from 2005/6 for NLCD 2006, NAIP 2008 for CDL 2008, NAIP 2009 for CDL 2009 and 2010 and NAIP 2011 for CDL 2011. DOQQs are either panchromatic black and white or color infrared images, depending on the county, with a 1 meter pixel. NAIP imagery is RGB imagery with 1 m pixel (0.5 m for some NAIP 2006 images). Image quality proved sufficient for photo interpretation but it proved very difficult to distinguish between row crops and pastures, especially when a picture was taken outside the growing season. This was among reasons we chose to use the European definition of "agricultural land".

Data for object creation

Object Based Image Analysis is an increasingly popular method for extracting information. Using objects vectorizes the raster land cover dataset, which also facilitates aerial photo interpretation of extensive areas. There have been various studies that have used objects to improve the quality of land cover datasets. These include cadastral parcels (Duvernoy 2000; De Wit & Clevers 2004; Raclot et al 2005; Serra et al 2009; Carmona et al 2010; Recio et al 2011), manually or automatically delineated farm plots (Heipke & Straub 1999; Walter 2000; Cohen & Shoshany 2002; Walsh et al 2004; Kokkinidis 2007), and image segmentation objects derived from specialized software (Ait Belaid et al 1992; Conrad et al 2010). Our approach was to use data and information as readily available as possible. We chose not to use CLU polygons because they are kept confidential and their distribution is limited (USDA FSA 2010). Specialized image segmentation software is expensive and not readily available, optimization of segments takes significant time and segments produced have similar area for each iteration which is not true for farm plots our the study area (Tong et al 2012). Thus we selected cadastral parcels as our objects, which in the region are tax parcels.

Cadastral parcels have several advantages. They are anthropogenic in nature, as are farm plots. Their limits, often but not always, correspond to farm plots. They are unambiguous and exist independently of image manipulation and classification. Unfortunately they also have issues. They are not fixed in time, owners and county agents can divide or unify parcels following property transactions. Also public roads and water bodies are often without a parcel. Furthermore in Henrico county there are many overlapping parcels that covered the same area. Among our objectives were to judge the quality of cadastral parcels for such use. Cadastral parcels are available at the website of each county, free of charge for Albemarle and for a price in the other three. We used parcels corresponding to 2011 for the entire timeframe of the study. We split multipart parcels into separate polygons and cleaned up all parcels using the clean-up function of Spatial Analyst to improve quality.

Creating test and validation layers

To validate the quality of the agricultural portion of land cover layers, they were reduced to a simple agricultural/non-agricultural land scheme with agricultural land (table 2) in one category and all other classes in the other. Articles of comparison were points and cadastral parcel delineated objects of the land cover layer. To create the test point layer we selected four hundred points over each county using the “Create Random Points” function of Spatial Analyst in ArcGIS 10.0. The land cover class label of the pixels that corresponded to each point for each layer for all the layers was extracted using Spatial Analyst and reduced to the agriculture/not agriculture scheme. This dataset is from now on referred to as the “Pixel” dataset. To create test polygons we used the zonal statistics tool in Spatial Analyst. Each specific dataset was harmonized to the table 1 scheme and parcels were labeled agricultural land if the majority class for each one was agricultural land, which caused small changes in the percent distribution of agricultural land for each year. This is from now on referred to as the “Parcel” dataset.

Two reference validation datasets were used in this study, a validation point layer created through photointerpretation of the 400 random points in each county and a validation parcel layer created through photointerpretation of select cadastral parcels. For the reference pixels we created a label for each of the years of the dataset through photointerpretation of each point in the reference imagery. For the reference polygons we photointerpreted all cadastral parcels that in the Parcel layer we classed as Agriculture or Grassland (a common confusion error) in any of the datasets. We also conducted spot checks over the entire county areas to determine if there were majority agricultural parcels that had not been classified in these two categories by any of the datasets. We further photointerpreted the parcels where the random points fell, thus also allowed us to independently judge if a significant number agricultural polygons had been completely missed by all the land cover datasets. This reference polygon dataset is from now on referred to as the “Photo” dataset.

On whether there was majority cover or not we used the generally used 50% rule making at times judgment calls (Figure 2), using the scheme given on table 3 that takes into account changes that took place within the polygons. Polygons that we judged not to host agriculture during any part of the study period are labeled "Never Agriculture", while those that were majority agricultural land during the entire study period are labeled "Always Agriculture". If there was agriculture throughout the time period and its extent within each parcel appeared to have increased or decreased, we note it as "Always Agriculture +" and "Always Agriculture –" respectively. If the cadastral plot appears to have been completely lost to agriculture (most often due to urbanization) or there was agricultural expansion and the plot entered agriculture (usually from forest clearing) we note it as "Lost to Agriculture Year1/Year2" or "Added to Agriculture Year1/Year2" where Year 1 is the date of the last image in which the plot appeared to host agricultural land and Year 2 is when it appears to have been converted to another use. Finally we also note plots that were "Lost to Afforestation", when we could not judge what year they were last used as agricultural land and "Other" when it followed several other trajectories which do not fit into the framework above.

Tracking change across time

The Photo layer is the dataset that tracks the area and distribution of agriculture across time more accurately than any of the specific test layers. For this reason we used interannual comparisons to track changes in agricultural land across the years, both in terms of extent and location. We also compared extent of agriculture derived from this layer with what is reported in the Census of Agriculture (USDA NASS 2009).

Comparing test and reference datasets

Three comparisons reveal the differences between test and reference data sets: (a) point to point comparison of the test Pixel and the reference pixel labels, (b) point to polygon comparison of the Pixel and the Photo labels and (c) polygon to polygon area comparison of the area in the Parcel and the Photo polygons. The unit of our comparisons is the proportion of agricultural land in each dataset. Proportion in point datasets is the proportion of the points in the agricultural land class compared to the number of all points. For Parcel and Photo datasets proportions are calculated by adding the area of all polygons labeled agricultural land and dividing by the area of each county as given by the US Census Bureau.

Point to Point comparison

The layers were first assessed using the standard approach of comparing the labels of the land cover layers for randomly selected pixels against their labels in the reference pixel imagery. Furthermore the results were used to calculate true area estimates and standard error (two standard deviations, 95% confidence level) of each classification using the marginal proportion method of Card (1982).

Point to Polygon comparison

The purpose of this validation is to form a bridge between point to point and polygon to polygon validation and to investigate the error that is introduced when using cadastral polygons as the unit of analysis. The label of the data pixel was compared to that of the Photo polygon it fell on. In cases the point did not fall into one unique cadastral plot, it was labeled non-agricultural.

Polygon to Polygon area comparison

We compared the labels of the Pixel and Photo datasets, noting errors of omission and commission. For this dataset though we do not report overlap (or lack of) of labels but overlap of cadastral parcel area.

Results

Assessing Quality

To assess the quality of the land cover layer we compared the proportion of agricultural land as a fraction of each county's area from the reference and test datasets, along with Card's (1982) marginal proportion and confidence intervals (figures 3 to 6). The extent of agriculture differs over time in each county, with Pixel and Parcel datasets experiencing significant fluctuations but less so for the Photo and marginal proportion datasets. While each county has its own characteristics, Pixel and Parcel datasets for all four counties show higher proportion of agriculture in 2001 compared to 1992, a peak in the proportion of agricultural land in CDL 2002, a reduction to the proportion in 2006 followed by an increasing trend up to 2010 and closing with a decrease in 2011. Differences in the extent for agricultural land for parcel and pixel are dramatic; in Chesterfield county agricultural land appear to triple between 2001 and 2002 and be reduced to 1/3 its 2002 value for 2006. The Photo layer, which we use as the reference layer, does not follow this trajectory. Changes across the 19 years are within a short range of 2% or less of the area of each county. Marginal proportion area, also fluctuates within the narrow range of 2% but is consistently lower than for the rest of the datasets, showing that some of the other datasets overestimate the extent of agriculture. For Albemarle and Chesterfield counties the extent of agricultural land according to the Photo layer falls within the confidence interval (the error bars) of the marginal proportion layer, for Charles City and Henrico counties it does not.

CDL 2002 suffers from errors of omission and commission so high that its use should be avoided, at least for our study area (tables 4-7). For the rest of the datasets the spatial extent of agricultural land is more accurate and for CDL improves with time. CDL 2008 underestimates the extent of agricultural land in all 4 counties, but this could be due to phenology since the 2008 growing season rainfall was well below average. Also note that CDL 2008 was created after CDL 2009, thus it was more difficult for NASS to validate and correct it. Figures 3 to 6 show a trend of improving quality on the CDL datasets with some outliers, such as Albemarle and Henrico Counties in 2009 and 2010 and Charles City in 2011. For NLCD, accuracy is best for 2006 while for the retrofit layer 1992 data appears more accurate than 2001 data.

Cadastral parcels as units of analysis

We next consider the use of cadastral parcels as polygon objects of analysis and try to understand the change introduced to both the test and the validation datasets. Quality and coverage of the cadaster differs for each county as related to how the cadaster was assembled in each specific county and the proportion of land that is included in parcels (table 8). Out of a total of 1600 random points in all four counties, 116 did not belong to any cadastral parcel. Only one of those, located in Henrico county, was agricultural land at any point during the study period. The use of parcels rather than pixels caused small changes in the percent distribution of agricultural land for each year. In Albemarle, Chesterfield and Henrico counties Parcel proportion is lower than Pixel proportion for the majority of the years while in Charles City County it is higher. The reference layers were also affected leading to different accuracy percentages depending on the validation method (tables 4 – 7). The use of the Photo label rather than the reference pixel label for validation consistently reduces the accuracy of the validation. Lowest error percentages were found in the parcel area comparison. Datasets with a high error of omission tend to have low errors of commission and vice versa. In the suburban Chesterfield and Henrico counties there are very significant errors in the extent of agriculture for all of the years and the validation methods. On the other hand in Charles City, and even more so in Albemarle county, all measure of accuracy were higher. It seems that as the extent of agriculture in each county increases, so does the accuracy of the agricultural land layers.

In general, the vast majority of "Always Agriculture" parcels appeared in the reference imagery to be cover by agricultural land to a very high extent, in the order of 70% or more. The cases where a judgment call had to be made because the proportion of agricultural land was close to 50% were limited. Still, the decision to categorize validation by the majority inside the cadastral parcel left a number of pixels miscategorized. To understand the magnitude of this error we compared the equivalent fraction of non-agricultural pixels from the reference pixel layer lying in agricultural parcels according to the Photo layer with agricultural pixels of the reference pixel layer in non-agricultural parcels (table 9). The proportion and area of non-agriculture points inside agricultural polygons is greater than the proportion of agricultural pixels inside non-agricultural polygons. The table shows that area comparisons based on cadastral polygons appear to have a systematic bias that overestimates the actual area of agriculture in all four counties. This finding is supported by the consistently lower values that marginal proportion gives for agricultural land compared to the Photo layer.

Change detection

Our final results address detection of change in the location and area of agricultural land in the ground across the 19 years studied. Change was limited in all of the counties (Table 10). The vast majority agricultural parcels fell in the "Always Agriculture" category. The main cause of loss of agricultural land was urbanization, secondary secession to forest and wetland restoration were present but very rare for the time period studied. The main source for agricultural expansion was forest clearing. In the imagery timber harvest is obvious but often the land is left to regrow new forest rather than converted to farmland. Multitemporal information is required to differentiate between new farm plots and timber harvest. Due to the unavailability of such information for the later datasets, new farm plots converted from forest after 2006 could not be identified.

From the Photo dataset, using the data from table 10, it seems that Albemarle county had the largest extent of agriculture both in terms of proportion (23.03%) and in absolute numbers (43276.8 ha) in 1992. It lost 577.2 ha or 1.3% by 2011. The largest proportional loss was in Chesterfield county (11.6% of

1992 farmland or 422.9 ha) but from a very low absolute (3614.6 ha) and relative (3.18%) extent. Loss in Henrico county was the largest in absolute figures (739.0 ha) but was less in proportion (9.7%) than in Chesterfield county. In Charles City County the extent of agriculture in 2011 is higher than in 1992 by 322.8 ha or 3.7%. Conversion of forest to agriculture outpaces the limited urbanization of agricultural land in this county.

Another source of information on the extent agricultural land and how it changes is the Census of Agriculture. Table 11 lists the extent of land in farms and the extent of cropland for the four counties according to the 1992, 1997, 2002 and 2007 CoA. For comparison we have also included Photo data from 1995, 2003 and 2008. In the CoA NASS does not follow the same definition of agricultural land as we do, which is one of the causes of the discrepancies between these two datasets. In general the extent of agriculture according to the Photo layer lies between the "land in farms" and "total cropland".

Discussion

Assessing quality

Each of the comparisons gives a different accuracy assessment percentage with parcel to parcel comparison showing less error that pixel to pixel and pixel to parcel. Overall accuracy appears to be high in the point validations (tables 4-7) but this reflects that non-agriculture is the majority of all four counties (figures 3-6, table 10). Each dataset differs in quality temporally and spatially but they all had a similar rank of accuracy for all counties for the same year; that is we did not see the phenomenon where one dataset was best for one county but worst for the rest. All land cover layers performed better in Albemarle and Charles City Counties that have high agricultural land cover and poorly in the suburban Chesterfield and Henrico counties. For these urban counties all datasets overestimated the extent of agriculture with the exception of NASS CDL 2008, which also underestimated the extent of agriculture in the other two counties. Aerial interpretation of the cadastral polygons showed that a common confusion error for polygons classified as majority agricultural land in the Parcel layer was single family detached houses with lawns.

Polygon to Polygon area comparison shows much smaller errors than the point validations. However it seems that the Photo layer overestimates agriculture, especially when compared to marginal proportion, something also supported by table 9. Marginal proportion percentages, which generally match those of the reference pixel layer, are a statistically robust method to estimate the area of each land cover class. However it does not give the location of the pixels of each class, thus making it difficult judge errors of omission and commission. Table 9 and the difference between the Photo and the marginal proportion values in figures 3 to 6 show that systematic overestimation of agricultural land was introduced when parcels were used as units of analysis, however more work is needed to understand and quantify this error.

The difference among datasets over the extent of farmland is consistent with the reviewed literature which showed that no dataset validation for agricultural quality performed well in areas of mixed land use (Maxwell et al 2008, Johnson 2013). This is supported by the increasing accuracy of the agricultural land dataset as the extent of agriculture in the county increases (tables 4 to 7). Another issue to note is that cadastral parcels are far from uniform, considering them uniform plots of land introduces errors of their own that affect the quality of validation as shown on table 9.

Cadastral parcels as units of analysis

We introduced the use of parcels to smooth the radical differences given by raw pixel comparison and facilitate the extraction of agricultural land at the field level from each layer across the years and within each year. By selecting the majority land cover of each polygon and keeping the same polygon boundaries for all layers, we reduced the heterogeneity introduced each year due to image coregistration errors, phenological differences, differences due to different pixel size and projection and other such apparent changes that do not correspond to actual changes on the ground across the years but only to classification artifacts. It tended to reduce errors of the pixel dataset over the extent of agriculture, since farms tend to be part of the same cadastral parcels. On the other hand it can include land such as riparian buffers that are not agricultural land in the definition we used. It facilitated complete photointerpretation of each county since the county is reduced from millions of pixels to a few thousand parcels that can be evaluated. However, as mentioned earlier, it introduced systematic overestimation of agricultural land in the parcel dataset. We cannot judge what part of this error was due to the act of changing the unit of analysis, what was due to the quality of the cadastral parcel layer as maintained by each county and what was due to the nature of the cadaster as a human denominated dataset that typically includes different land covers with the same functional land use.

When studying cadastral dataset quality we saw that the large aquatic extent of Charles City County meant that significant parts of it were not part of the cadaster. On the other hand it was the abundance of public roads in suburban Chesterfield and Henrico County that led to its comparatively low coverage by the cadaster. In Henrico county properties in buildings owned by multiple owners were mapped in parcels having different identity numbers but the same spatial extent. This led to the cadaster having a larger spatial extent than the county, despite it not covering roads and water bodies. It is in landlocked and rather rural Albemarle county that the cadaster functioned best as the unit of aggregation.

Stehman and Wickham (2011) compared accuracy derived from pixels, block of pixels and polygons as units of comparison. They mention that polygons are often viewed as the more natural validation choice in that they correspond to features on the landscape provided that the polygons are defined by the reference classification, as happens in our study where cadastral parcels preexist, rather than the map classification. Their finding was that accuracy varied for the same map and reference data depending on the validation method, with bigger differences found in the rarer classes. Our findings agree with Stehman and Wickham. Agricultural land was not the majority in any of the counties and was very rare in the two counties surrounding Richmond.

Changes in the extent of agriculture

Both the Photo layer and marginal proportion show that there were only small changes in the extent of agricultural land in the counties. It seems that while farmers change the distribution and extent of specific crops they grow most of the years, they select the same plots of land to grow them on. It seems that agriculture in our study area was not sufficiently profitable to drive large scale deforestation; for that matter we did find several parcels in each county that were lost to afforestation. Also urbanization preferentially chose forested rather than agricultural land for urban expansion, although we noted the higher losses in the already suburban Chesterfield and Henrico counties. Due to our decision to reduce classifications to Anderson level I, so as to compare various datasets, we were not able to track specific crops. In any case NLCD only classified agricultural land, not specific crops. The core of agricultural land remained the same in each county for all the years, as shown by the relative extent of the "Always Agriculture" category compared to the other agricultural land categories in table 10. There were additions and subtractions to agricultural land, but they were not as dramatic as the Pixel layer shows.

Extraction of actual agricultural land covers requires more work than the use of a single land cover dataset and there has been work towards that goal (Boryan et al 2012; Johnson 2013). Considering that change in the area and location of agriculture has been so low over the 19 years studied, it should be possible to create a high quality dataset combining multiple year datasets that is more accurate than each specific dataset for the year it refers to, as Johnson (2013) has done for the entire United States.

Conclusion

Validation of several high resolution agricultural land cover layers over four eastern Virginia counties revealed that clear definitions of land covers to consider as agricultural land are required for consistency in interpretation. Accuracy was higher in the less urbanized counties (Albemarle and Charles City) rather than the outskirts of Richmond. NLCD 1992, 2001, 2006 and CDL 2009, 2010 and 2011 had high accuracy while CDL 2002 and 2008 show low accuracy. It is possible that phenological differences due to the dryness of 2008 have negatively affected its accuracy. The use of cadastral parcels to improve the delineation of the land cover dataset stabilized the apparent extent of agriculture from the changes that pixel comparison showed and permitted multitemporal evaluation of specific plots of land but introduced errors of its own, most important being a systematic overestimation of agricultural land. Future researchers should balance the specific advantages and disadvantages that the use cadastral parcels brings in their research. Change in the extent of agriculture over the 19 years studied proved rather small. There is still significant work that can be pursued over both the extent of agriculture and validation of land cover layers. Findings on the extent of agricultural land from photointerpretation showed different values and patterns than the Census of Agriculture statistics. It seems that in the heterogeneous and humid landscape of Virginia attempts to extract the location and extent of agricultural land will result in a product of low quality especially as the extent of agriculture diminishes. If attempting to extract agricultural land cover in an area where it is a rather fixed minor component of the landscape such as Virginia, we suggest that some sort of ancillary data or classifications referring to multiple times to improve product accuracy.

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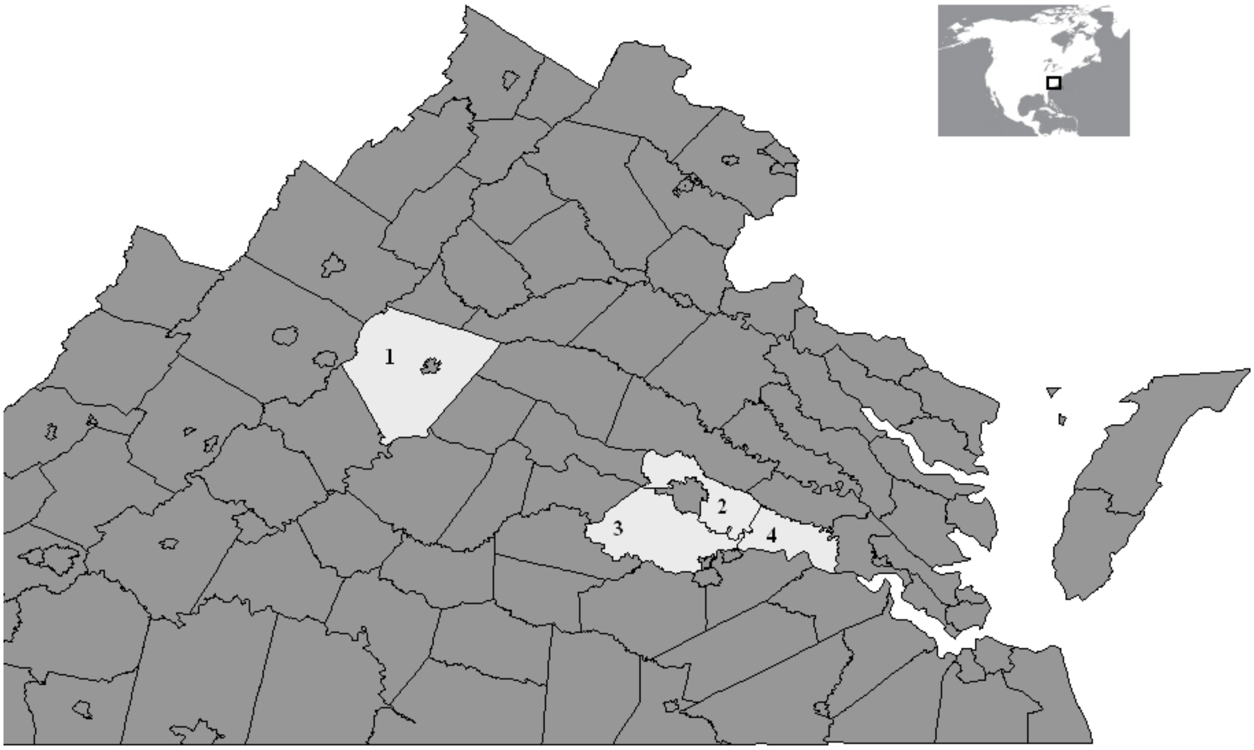

Figure 1. The four counties of the study area: 1. Albemarle 2.Henrico 3. Chesterfield 4. Charles

City

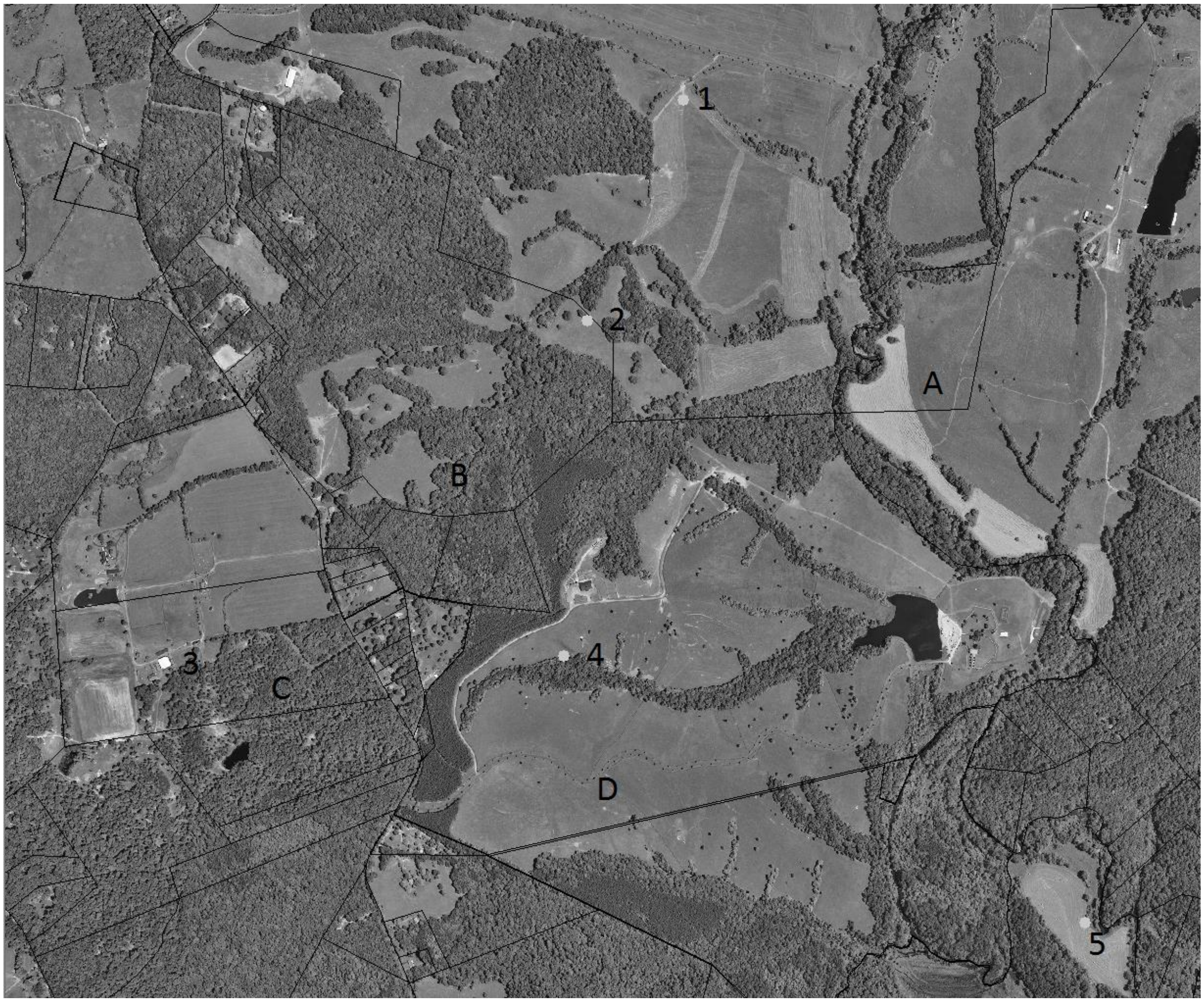

Figure 2. Example of the random validation points over the cadastral polygons. Point 1 is an agricultural point over majority agricultural polygon A. Point 2 is an agricultural point over majority non agricultural polygon B. Point 4 is non agricultural point over majority agricultural polygon D. Notice how polygons A, B, C and D differ substantially in size

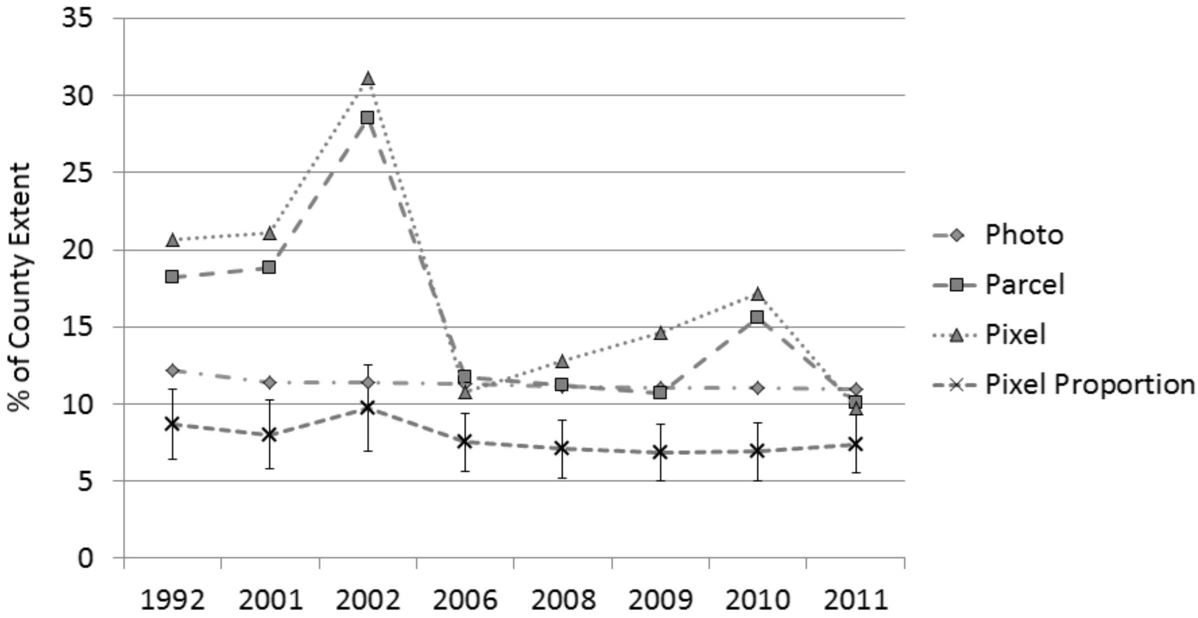

Figure 3. Percentage of Albemarle County covered by agriculture by dataset. Photo: validated percentage of agriculture as per photointerpretation. Parcel: percentage of the county having parcels with majority agricultural land. Pixel: percentage of agriculture pixels. Pixel proportion: marginal proportion of the county in agriculture derived as per Card (1982) with error bars at 2 standard errors. Note that when precision of the estimates is taken into account there essentially are no differences in agricultural land extent among the years

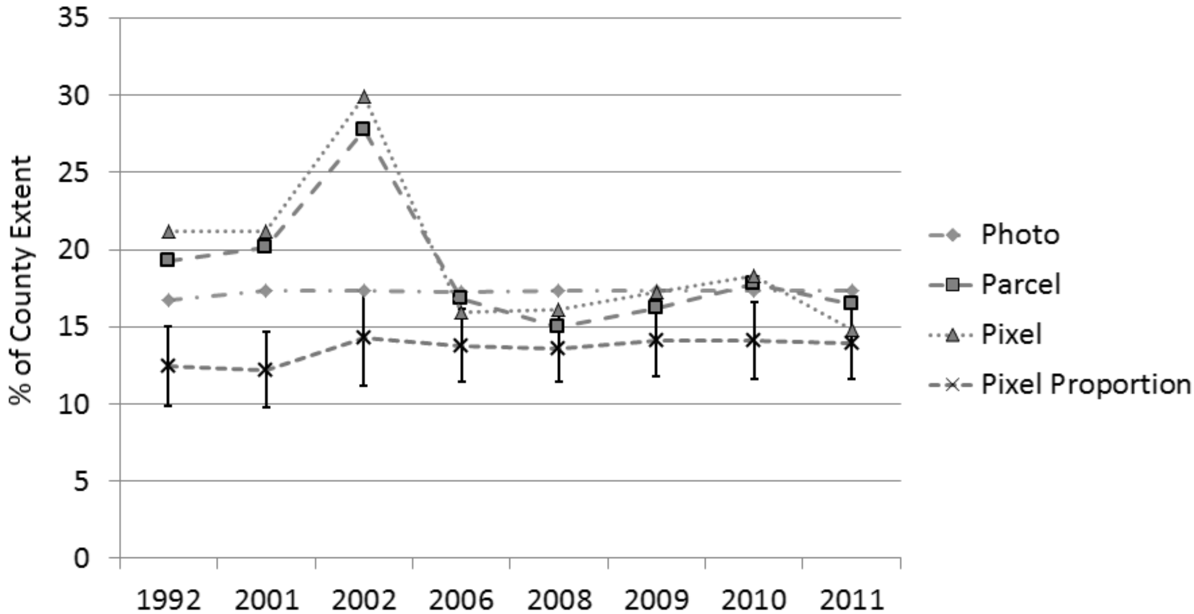

Figure 4. Percentage of Charles City County covered by agriculture by dataset. Photo: validated percentage of agriculture as per photointerpretation. Parcel: percentage of the county having parcels with majority agricultural land. Pixel: percentage of agriculture pixels. Pixel proportion: marginal proportion of the county in agriculture derived as per Card (1982) with error bars at 2 standard errors. Note that when precision of the estimates is taken into account there essentially are no differences in agricultural land extent among the years

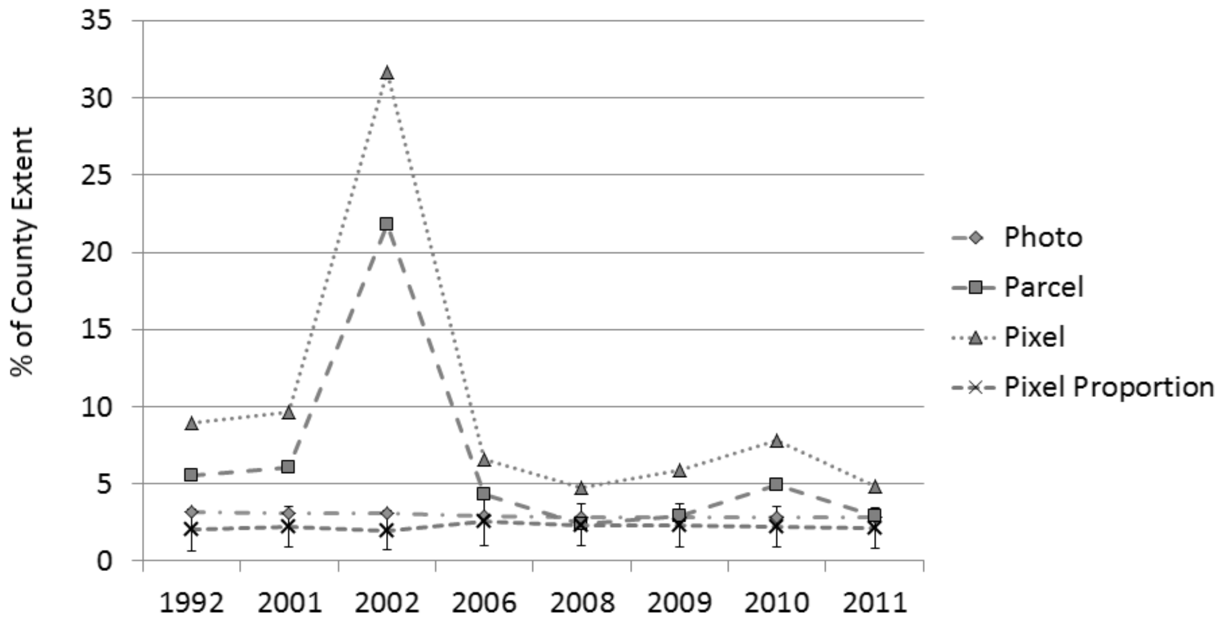

Figure 5. Percentage of Chesterfield County covered by agriculture by dataset. Photo: validated percentage of agriculture as per photointerpretation. Parcel: percentage of the county having parcels with majority agricultural land. Pixel: percentage of agriculture pixels. Pixel proportion: marginal proportion of the county in agriculture derived as per Card (1982) with error bars at 2 standard errors. Note that when precision of the estimates is taken into account there essentially are no differences in agricultural land extent among the years

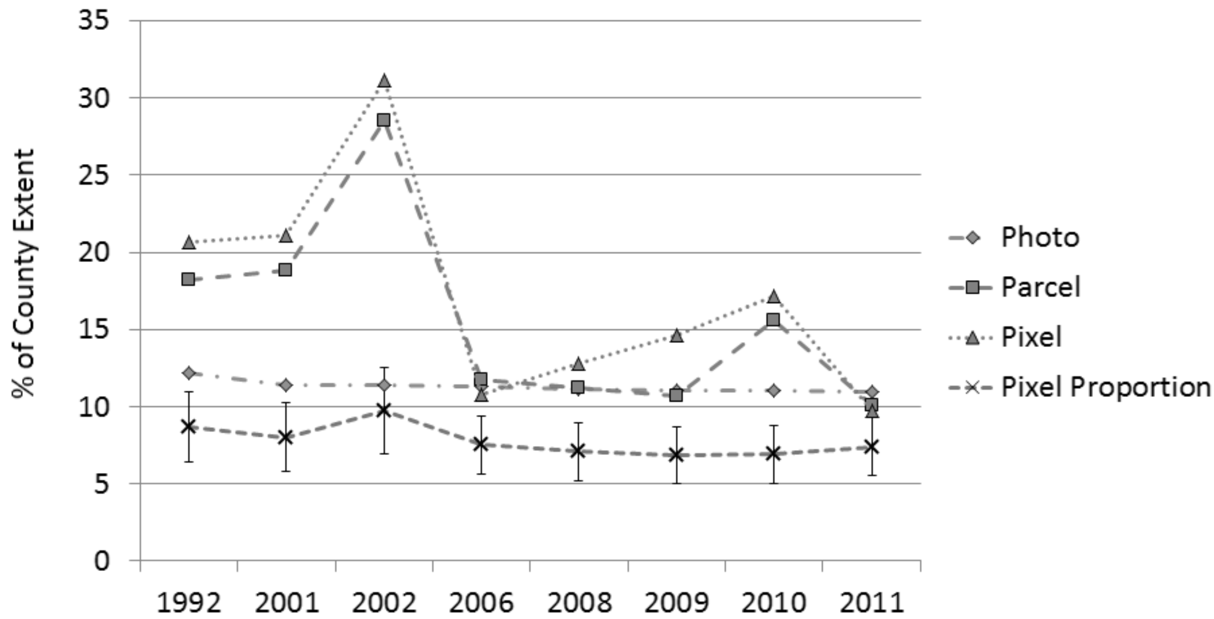

Figure 6. Percentage of Henrico County covered by agriculture by dataset. Photo: validated percentage of agriculture as per photointerpretation. Parcel: percentage of the county having parcels with majority agricultural land. Pixel: percentage of agriculture pixels. Pixel proportion: marginal proportion of the county in agriculture derived as per Card (1982) with error bars at 2 standard errors. Note that when precision of the estimates is taken into account there essentially are no differences in agricultural land extent among the years

Harmonized Class	Description
0	Unclassified, Clouds
1	Open Water
2	Urban
3	Barren
4	Forest
5	Grassland/ Shrubland/ Rangeland
6	Agriculture
7	Wetlands
8	Ice/Snow

Table 1. Modified Anderson Level I classification used in this study

Land Cover Dataset/Year	Classes for Agriculture
NLCD 1992-2001 retrofit for 1992	6,61,62,63,64,65,67,68
NLCD 1992-2001 retrofit for 2001	6,16,26,36,46,56,76,86
NASS CDL 2002	1 – 59, 61, 62, 67 – 80, 100 - 103
NLCD 2006	81, 82
NASS CDL 2008	1 – 62, 66 – 77, 181, 204-254
NASS CDL 2009	1 – 62, 66 – 77, 181, 204-254
NASS CDL 2010	1 – 62, 66 – 77, 181, 204-254
NASS CDL 2011	1 – 62, 66 – 77, 181, 204-254

Table 2. Lookup table for agricultural class for the datasets used

Validation Class	Definition
Never Agriculture	Plot where agriculture never took place or, if it did, it never surpassed 50% of its extent
Always Agriculture	Plot that has been always agricultural from 1995 to 2011 and the same extent of it was cultivated all of the years
Always Agriculture +	Plot that has always been agricultural from 1995 to 2011 but the extent of agriculture within the plot has increased
Always Agriculture -	Plot that has been agricultural from 1995 to 2011 but the extent of agriculture within the plot has decreased
Lost to Agriculture 1995-2003	Plot that was agricultural in 1995 but urban since 2003
Lost to Agriculture 2003-2006	Plot that was agricultural in 2003 but urban since 2006
Lost to Agriculture 2006-2008	Plot that was agricultural in 2006 but urban since 2008
Lost to Agriculture 2008-2009	Plot that was agricultural in 2008 but urban since 2009
Lost to Agriculture 2009-2011	Plot that was agricultural in 2009 but urban since 2011
Lost to Afforestation	Plot that was agricultural in 1995 but farming was eventually abandoned leading to afforestation
Added to Agriculture 1995-2003	Plot that was added to agriculture between 1995 and 2003
Added to Agriculture 2003-2006	Plot that was added to agriculture between 2003 and 2006
Added to Agriculture 2006-2008	Plot that was added to agriculture between 2006 and 2008
Other (Agriculture 92)	Plots that were agricultural at some point but followed a land
Other (Not Agriculture 92)	cover trajectory not consistent with previous classes

Table 3. Validation classes used for manual photointerpretation

Dataset	Point to point			Point to Polygon			Polygon to Polygon Area	
	Error of Commission	Error of Omission	Overall accuracy	Error of Commission	Error of Omission	Overall Accuracy	Error of Commission	Error of Omission
NLCD 1992	30.53%	19.51%	88.75%	43.16%	41.30%	80.25%	6.22%	12.37%
NLCD 2001	27.08%	16.67%	90.00%	42.71%	37.50%	81.50%	6.28%	11.42%
CDL 2002	46.49%	28.24%	80.75%	51.75%	38.20%	76.75%	23.58%	17.28%
NLCD 2006	28.57%	25.93%	88.75%	42.86%	45.45%	81.00%	6.87%	14.16%
CDL 2008	27.27%	31.71%	88.25%	44.16%	51.14%	81.00%	5.58%	33.46%
CDL 2009	27.38%	25.61%	89.00%	39.29%	42.05%	82.50%	5.79%	22.34%
CDL 2010	26.67%	19.51%	90.00%	41.11%	39.77%	82.00%	7.24%	14.73%
CDL 2011	25.56%	17.28%	90.75%	40.00%	38.64%	82.50%	6.79%	15.74%

Table 4. Comparison of errors of commission and omission for all three validation methods in Albemarle county

Dataset	Point to point			Point to Polygon			Polygon to Polygon Area	
	Error of Commission	Error of Omission	Overall accuracy	Error of Commission	Error of Omission	Overall Accuracy	Error of Commission	Error of Omission
NLCD 1992	48.35%	11.32%	87.50%	52.75%	29.51%	83.50%	20.39%	8.31%
NLCD 2001	47.25%	7.69%	88.25%	52.75%	29.51%	83.50%	22.34%	9.70%
CDL 2002	57.01%	11.54%	83.25%	57.01%	24.59%	81.00%	39.74%	3.47%
NLCD 2006	27.59%	17.65%	93.75%	37.93%	40.98%	88.25%	11.23%	14.15%
CDL 2008	25.00%	11.76%	94.75%	41.67%	42.62%	88.25%	8.52%	21.01%
CDL 2009	27.87%	13.73%	94.00%	40.98%	40.98%	87.50%	10.45%	16.57%
CDL 2010	32.31%	13.73%	93.00%	40.00%	36.07%	88.00%	15.25%	13.01%
CDL 2011	22.64%	19.61%	94.50%	37.74%	45.90%	88.00%	6.36%	11.28%

Table 5. Comparison of errors of commission and omission for all three validation methods in Charles City county

Dataset	Point to point			Point to Polygon			Polygon to Polygon Area	
	Error of Commission	Error of Omission	Overall accuracy	Error of Commission	Error of Omission	Overall Accuracy	Error of Commission	Error of Omission
NLCD 1992	82.86%	25.00%	92.25%	94.29%	71.43%	90.50%	59.34%	29.50%
NLCD 2001	79.49%	11.11%	92.00%	87.18%	37.50%	90.75%	61.31%	23.86%
CDL 2002	93.71%	0.00%	69.00%	95.10%	12.50%	68.25%	87.37%	11.24%
NLCD 2006	76.19%	44.44%	95.00%	90.48%	75.00%	93.75%	54.82%	32.95%
CDL 2008	66.67%	33.33%	96.25%	83.33%	57.14%	93.75%	42.96%	52.55%
CDL 2009	73.91%	33.33%	95.00%	86.96%	57.14%	94.00%	49.98%	48.40%
CDL 2010	78.13%	22.22%	93.25%	87.50%	42.86%	92.25%	59.11%	27.97%
CDL 2011	71.43%	33.33%	95.50%	80.95%	42.86%	95.00%	42.29%	40.40%

Table 6. Comparison of errors of commission and omission for all three validation methods in

Chesterfield county

Dataset	Point to point			Point to Polygon			Polygon to Polygon Area	
	Error of Commission	Error of Omission	Overall accuracy	Error of Commission	Error of Omission	Overall Accuracy	Error of Commission	Error of Omission
NLCD 1992	63.27%	10.00%	83.50%	63.27%	28.00%	81.00%	40.61%	10.81%
NLCD 2001	67.00%	10.81%	82.25%	67.00%	28.26%	80.00%	43.66%	7.11%
CDL 2002	73.50%	16.22%	77.00%	73.50%	32.61%	74.75%	60.93%	2.48%
NLCD 2006	42.00%	14.71%	93.50%	40.00%	31.82%	91.50%	24.59%	21.98%
CDL 2008	50.82%	9.09%	91.50%	52.46%	30.95%	91.50%	22.27%	21.41%
CDL 2009	56.76%	5.88%	89.00%	59.46%	28.57%	86.00%	29.27%	31.27%
CDL 2010	61.18%	2.94%	86.75%	62.35%	23.81%	84.25%	38.18%	12.02%
CDL 2011	40.00%	18.18%	94.00%	40.00%	34.15%	92.00%	15.60%	22.52%

Table 7. Comparison of errors of commission and omission for all three validation methods in Henrico county

County	Spatial Extent (ha)	Sum of cadastral parcels (ha)	Number of points without a parcel	Number of points on multiple parcels
Albemarle	187932.7	186221.5	4	0
Charles City	52753.1	46871.4	42	0
Chesterfield	113560.7	106466.6	30	0
Henrico	63000.4	81029.5	42	13

Table 8. Cadastral parcel accuracy characteristics

County	Description	%	Relevant Polygon Area (ha)	Equivalent Area (ha)
Albemarle	Points Never Ag inside Ag Polygons	27.17	43913.2	11932.9
	Points Ag inside Never Ag polygons	6.17	142308.3	8778.8
Charles City	Points Never Ag inside Ag Polygons	34.43	9282.8	3195.7
	Points Ag inside Never Ag polygons	4.07	37588.7	1529.0
Chesterfield	Points Never Ag inside Ag Polygons	33.33	3711.3	1237.1
	Points Ag inside Never Ag polygons	1.11	102755.3	1138.6
Henrico	Points Never Ag inside Ag Polygons	26.00	7818.0	2032.7
	Points Ag inside Never Ag polygons	1.69	73211.5	1240.9

Table 9. Accumulative errors of omission and commission due to the use of polygons for validation rather than points

Parcel Type	Albemarle	Charles City	Chesterfield	Henrico
Total	186221.5	46871.4	106466.6	81029.5
Never Agriculture	142308.3	37444.5	102762.9	73313.4
Always Agriculture	40185.9	7714.9	2643.2	6374.0
Always Agriculture +	1338.7	668.2	220.8	44.1
Always Agriculture -	548.4	462.1	274.1	238.3
Lost Ag 95 03	533.0	74.1	143.2	376.8
Lost Ag 03 05/6	375.3	20.7	53.1	120.9
Lost Ag 05/6 08	66.0	13.3	88.2	150.1
Lost Ag 08 09	50.0	1.6	24.3	17.1
Lost Ag 09 11	17.9	0.0	12.3	29.2
Lost to Afforestation	129.1	19.3	147.8	93.5
Added to Ag 95 03	428.6	381.6	78.7	112.5
Added to Ag 03 05/6	192.1	10.8	11.2	49.0
Added to Ag 05/6 08	0	59.8	0.0	0.0
Other (Ag 92)	32.6	0.4	0.0	110.7
Other (Not Ag 92)	15.7	0.0	6.8	0.0

Table 10. Sum of the extent of all parcels in hectares belonging to the validation classes of table 3

Year		Albemarle	Charles City	Chesterfield	Henrico
1992 CoA	Land in Farms	76310.4	11665.9	7038.3	9793.8
	Total Cropland	35560.6	7325.2	3609.8	5855.0
1995 Parcel	Ag. Land	43276.8	8830.5	3614.6	7656.5
1997 CoA	Land in Farms	69707.6	(D)	8154.8	10684.9
	Total Cropland	30381.0	(D)	4202.3	5670.9
2002 CoA	Land in Farms	71809.5	11604.8	9434.0	11385.8
	Total Cropland	27949.6	7424.4	3912.9	6296.9
2003 Parcel	Ag. Land	43150.6	9137.6	3521.9	7202.8
2007	Land in Farms	64067.5	11124.4	8711.7	8132.6
2007	Total Cropland	18703.0	7427.2	2653.1	4943.6
2008 Parcel	Ag. Land	42767.4	9154.9	3229.8	6995.7

Table 11. Extent in hectares of land in farms and total cropland according to the Census of Agriculture and proximate relevant photointerpreted dataset for the four counties. Photointerpreted datasets were chosen to be as close as possible to the CoA. In Charles City County numbers were withheld in the 1997 Census of Agriculture due to low farmer response so as to preserve farmer confidentiality.

Calculating Ecosystem Services provided by agricultural land using GIS and Remote Sensing methods

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***Abstract*— For this study we use Geographical Information System and Remote Sensing methods to calculate some Ecosystem Services provided by agricultural land and make the case for its value and preservation. Our study area consists of Albemarle, Charles City, Chesterfield and Henrico counties in eastern Virginia. Each is facing different development pressures affecting their ability to provide ecosystem services. We link SSURGO soil mapping units with the VALUES agricultural productivity estimates to estimate realistic yield for 15 crops in actual agricultural land, as extracted from multiple years of the National Land Cover Database and the NASS Cropland Data Layer. We identify which farm plots are better suited for biofuel production without compromising local ability to produce sufficient food for the local population. Knowing farm productivity we can also calculate the Net Primary Productivity of agricultural land and compare it with other local land covers. Then we model the effects of agriculture on soil air carbon flows and carbon sequestration. Incorporating fertilizer recommendations and pesticide use models we calculate their quantities utilized and efficiency ratios. Finally we calculate economic outcome, impact and identify areas prone to change to and from agricultural production in the study area using the cost models given by Virginia Cooperative Extension publications. Our methodologies are based on readily available data and open information and can be used in other areas by different researchers. Our estimates can be improved through the use of better models.**

Keywords—Ecosystem Services, agriculture, Virginia, Net Primary Production, farm economic output, carbon fixation

I. Introduction

The most popular, but by no means fully accepted, definition for Ecosystem Services (ESS) is that by the Millennium Ecosystem Assessment team: “Ecosystem services are benefits people obtain from the ecosystem” [1]. Most studies focus on natural ecosystems and do not address services provided by agro-ecosystems. The purpose of this article is to provide quantitative values to a number of ESS provided by agricultural land through the use of Geographic Information Systems and Remote Sensing derived methods. Furthermore, in order to help provide further ESS from agro-ecosystems we identify land better suited to grow biofuels without compromising the ability to provide food for the local population and study the economics of agricultural production in four Virginia counties. We adopt a multitemporal approach in our study because conclusions based on single year studies can be influenced by atypical effects and because we wished to study multitemporal trends in ESS.

The majority papers dealing with ecosystem services and agricultural land tend to focus only on the negative consequences, e.g. [2]. Often agricultural land is compared undesirably to forests, without properly evaluation the full range of services it provides. Papers attempting to calculate ESS provided by agriculture are few. Costanza [3] made a systematic calculation of the monetary value of ESS in New Jersey, including those provided by agricultural lands. Prince [4] calculated Net Primary Production (NPP) from agricultural crops for the US Midwest. Chaterjee [5] calculated biofuel feedstock potential for the US and the cost on nutrients that this practice would impose. This paper integrates various methods available in the literature adapted for local Virginia conditions to calculate ESS. We hope that other researchers can adopt our methodology for their study areas.

A. Study Area

We chose to focus in four counties in eastern Virginia: Albemarle, Charles City, Chesterfield and Henrico (Fig. 1). These counties offer a snapshot of the different socioeconomic processes affecting agriculture in the Commonwealth of Virginia. Albemarle County surrounds the rapidly growing independent City of Charlottesville, which is not studied in this paper. While it still has a rural character, it is undergoing rapid population growth and urbanization. Chesterfield and Henrico

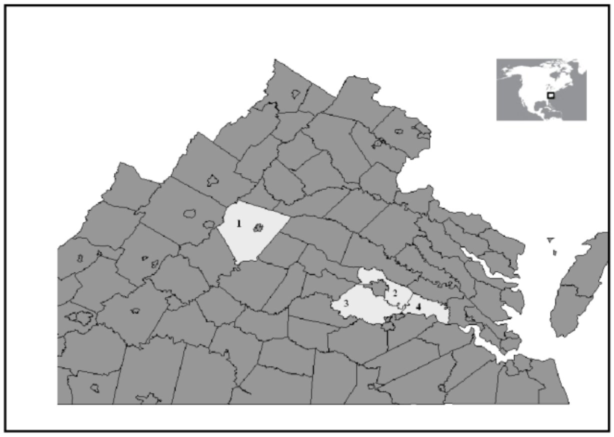

Fig. 1. Map of the eastern Virginia: 1. Albemarle 2.Henrico 3.Chesterfield 4.Charles City Counties

Counties surround the city of Richmond. They already have a suburban character and they have seen a rise in population, at a different rhythm of development for each, but at a slower pace than in Albemarle county. These three counties are considered part of the Piedmont. Charles City County is a very rural, sparsely populated agricultural Coastal Plain county that has not undergone significant land cover change over the last 20 years at least. Major crops grown in the counties are corn, soybeans, wheat (which comprise most of agriculture) barley, oats and sorghum. Other crops include cotton, tobacco, vegetables and sodgrass. Pastureland-grassland is the prevalent agricultural land cover in all four counties for all the years studied.

B. *Ecosystem Services*

The Millennium Ecosystem Assessment [1] divides Ecosystem Services into four categories: Supporting, Provisioning, Regulating and Cultural. For this paper in terms of supporting services we deal with NPP and Nutrient Cycling. Among provisioning services we deal with crop and biofuel production. Among regulating services we deal with carbon fixation as a precursor to sequestration. We do not study cultural services in this study. We do investigate though farm economic output so that we can have a monetary comparison for the value of ESS.

II. MATERIALS AND METHODS

A. *Datasets used*

The Soil SURvey GeOgraphical database (SSURGO) is a spatial database of the different soils found in an area. It is a digital version of the soil surveys conducted by the National Cooperative Soil Survey. All four counties have had a recent soil survey, which was one of the reasons they were chosen for this study. The Virginia Agronomic Land Use Evaluation System (VALUES) is a tool created by Virginia Tech and the Virginia Cooperative Extension to help manage farmland in Virginia[6]. It is a database of over 900 soil series grouped for management recommendation and realistic yield. VALUES has been updated several times, most recently in 2005 [7], and is currently available for 15 major crops.

The majority land cover in the study area is forest. Extracting the location of agricultural land can be achieved through the use of the remote sensing products that are available for the study area. Best suited are the highest resolution datasets available, more specifically the National Land Cover Database (NLCD) and the National Agricultural Statistical Service's Cropland Data Layer (NASS CDL). Kokkinidis et al [8] have created a validated dataset of agricultural land in the 4 counties using those particular datasets along with cadastral plot information. It is this dataset which we use in this study.

The US Department of Agriculture has several tools online that proved usefully for this study. The Economic Research Service has created Quickstats [9] which contains the extent and production of major crops grown in each county. The Crop Nutrient Tool [10] contains information on the nutrient content of grains and stem of major crops. The Fertilizer and Price Database [11] contains historical and current information on fertilizer prices. Finally the Virginia Cooperative Extension (VCE) has published farm economics information on the major crops cultivated in Virginia [12].

B. *Methods*

We combined VALUES and SSURGO, using soil series name as the unique key to join the databases, to create a unified spatial database of potential agricultural yield for each of the counties. Then we incorporated actual extent of agricultural land from the validated agricultural plot database. In order to determine specific crops grown in each farm plots we used the majority land cover category in each plot as derived from the CDL. To validate our result we compared crop extent and production numbers derived from CDL, SSURGO and VALUES with Quickstats for that particular year. We only worked with years for which CDL is available; those are 2002, 2008, 2009, 2010, 2011 and 2012. For several crops in all the counties for some of the years Quickstats did not have production figures available because NASS does not release numbers if they can compromise farmer confidentiality if too few farmers cultivate a crop.

To calculate NPP we used the methodology of [4], utilizing both the Quickstats actual crop production values and VALUES derived potential crop production values. To calculate above ground biomass we used local harvest indices (HI) from the research conducted by the Crop and Soil Environmental Science department of Virginia Tech [13],[14],[15]. Generally for HI we used the value 0.45 for small grains (wheat, barley) and 0.50 for the others field crops. For grasses we used a HI of 1, since VALUES potential yield for hay is that for all aboveground biomass. For root to shoot ratios we used values from [4] since local values were unavailable. All mass aspects of the crops were added and then moisture was removed to calculate NPP. To calculate NPP for pastures and grassland we used considered them to be covered with bermudagrass hay for Charles City County and tall fescue for the Piedmont counties. Then we calculated N, P and K content for the aboveground biomass using the Crop Nutrient Tool. We also calculate carbon fixation using a 0.45 ratio which is consistent with previous studies [16],[17],[18],[19].

With our methodology we can calculate the quantity of crops that can be grown locally. In order to calculate how many people can be fed, we would need a typical diet of the study region [20], which is currently unavailable. The general consensus is that lands that are marginal for crop production or byproducts that are not used for human or animal consumption in significant quantities such as stover, can be used for biofuel production without comprising the ability to grow food. VALUES divides soil series into five quality groups for crop yield depending on the crop. Generally soils have high or low productivity for all crops. We define low productivity soils as those belong in the VALUES III, IV, and V category in that soils belonging to these productivity groups are economically marginal for row crop production. For NPP calculations we used the productivity of the crops that CDL showed that were grown in the year it refers to, however these could easily be converted to biofuel crops to cover such needs.

VCE has published crop budgets which include nutrient estimates for various productivity levels. The nutrient recommendations are intended to be adapted to nutrient levels as the local soil tests demand. For cases where soil test values are unavailable, it includes nutrient values that it claims they correspond to nutrients removed by each crop during the growth cycle. A comparison with [10] shows that the fertilizer recommendations are in excess to nutrient removed by the grains or pods for all crops (Table I). This is understandable because often in addition to the grain other parts of the plant will be harvested accidentally or in purpose which will be removed during crop treatment. Since in the long term all nutrients need to be added by the farmer, especially since after a few centuries of intensive agriculture, Virginia soils are often depleted, we decided for the needs of the economic calculation to set fertilizer needs at 120% of Nitrogen needs (to cover volatilization) except for soybeans that can fix their own Nitrogen and at 100% of Phosphorus and Potassium needs. We used the farm gate price for the crops in Virginia from Quickstats to annualize farm proceeds, seed cost from FINBIN [21], fertilizer costs from [11] and the Central Atlantic (PADD 1B) No 2 Diesel Retail Prices (Dollars per Gallon) from the Energy Information Administration [22] for diesel cost from which we subtracted each year $0.60 to account for the difference between that cost and Virginia farmer's typical cost (farmer diesel in Virginia has several tax breaks compared to PADD 1B price). VCE crop budgets also include lime, herbicides, insecticides, fungicides, labor, insurance, repairs, depreciation and other costs. We have kept these figures constant for all the years since they have not changed significantly. For corn we used the minimum tillage budget, for soybeans the Round Ready minimum tillage budget, for, barley and wheat we used the intensive management budgets while for grain sorghum the minimum tillage budget. No budget was available for oats. Considering their limited spatial and temporal prevalence in the study area as revealed by NASS CDL their economic output was limited. Our choices reflect typical farmer agricultural practices of the study area.

TABLE I. RATIO OF VCE CROP BUDGET GUIDELINES TO GRAIN NUTRIENT REMOVAL FOR MAJOR CROPS

Crop	N	P	K
Corn	1.26	1.70	1.90
Soy	0.00	1.33	1.91
Wheat	1.39	1.41	1.84
Barley	1.49	1.57	1.88
Sorghum	1.20	1.48	1.21

III. RESULTS

A. *Suitability for biofuel production*

Table II contains the extent of actual agricultural land for all 4 counties and the share that is taken by VALUES quality category III, IV and V soils. There are several potential competing uses for low quality land especially since Virginia, due to its very large animal production sector has a shortage of feed. These particular lands though are already agricultural and not very viable economically, hence are well suited for bioenergy, pasture or hay crops.

B. *Net Primary Production, Carbon fixation and Carbon sequestration*

Tables III to VI contain calculations of NPP in the 4 counties for the crops actually grown as indicated by CDL along with carbon fixation. NPP for agriculture in Virginia is similar to that of a young fast growing temperate forest with no limiting factors in North Carolina [23] but requires nutrient inflows and intensive management. Since mature forests have lower NPP than fast growing forests and fast growing forests are not very capable of replacing assimilated nutrients, it is possible that compared to those conditions agriculture can have higher NPP than forests.

Sequestered carbon is carbon that was originally fixed by plants. The current framework for carbon sequestration however considers carbon sequestered only if it remains out of the atmosphere for at least 100 years [16], something that does not happen with agricultural products with very few exceptions (e.g. vintage wine). InFOREST [24] has an ecosystem services calculator which calculates carbon sequestered in a forest using the FVS model. We used the calculator for a mixed pine hardwood forest and a hardwood forest having the extent of

TABLE II. EXTENT OF ACTUAL AGRICULTURAL FOR ALL 4 COUNTIES AND PROPORTION OF LOW QUALITY LAND

County	Total extent	All farm	Low quality	% in farm	% low farm
Albemarle	187932.7	40509.9	22075.7	21.56%	54.49%
Charles City	52753.1	8825.3	4187.6	16.73%	47.45%
Chesterfield	113560.7	3170.9	2620.3	2.79%	82.64%
Henrico	63000.4	7006.1	3963.3	11.12%	56.57%

TABLE III. NPP AND FIXED CARBON FOR THE CROPS GROWN IN ALBEMARLE COUNTY

Year	Cropland Data Layer crop production		Quickstats crop production	
	NPP (Tons biomass)	*Fixed C (T)*	*NPP (Tons biomass)*	*Fixed C (T)*
2002	193645.0	87140.2	4463.1	2008.4
2008	279079.4	125585.7	NA	NA
2009	316941.0	142623.5	NA	NA
2010	324586.5	146063.9	2360.5	1062.2
2011	324395.8	145978.1	NA	NA
2012	322755.8	145240.1	NA	NA

TABLE IV. NPP AND FIXED CARBON FOR THE CROPS GROWN IN CHARLES CITY COUNTY

Year	Cropland Data Layer crop production		Quickstats crop production	
	NPP (Tons biomass)	*Fixed C (T)*	*NPP (Tons biomass)*	*Fixed C (T)*
2002	80082.8	36037.3	53036.4	23866.4
2008	83535.8	37591.1	70808.4	31863.8
2009	91077.2	40984.7	74211.3	33395.1
2010	90270.6	40621.8	42735.7	19231.1
2011	97438.9	43847.5	75750.4	34087.7
2012	103739.7	46682.8	66368.7	29865.9

TABLE V. NPP AND FIXED CARBON FOR THE CROPS GROWN IN CHESTERFIELD COUNTY

Year	Cropland Data Layer crop production		Quickstats crop production	
	NPP (Tons biomass)	*Fixed C (T)*	*NPP (Tons biomass)*	*Fixed C (T)*
2002	26628.4	11982.8	3576.1	1609.3
2008	13171.6	5927.2	3016.2	1357.3
2009	13575.9	6109.2	2023.0	910.4
2010	17928.2	8067.7	1494.3	672.4
2011	18444.0	8299.8	5195.4	2337.9
2012	17461.7	7857.7	3264.7	1469.1

agricultural land in each county and with a stand height of 1.52 m (5 ft) which is a typical height for annual crops (Table VII). The forest sequestered carbon figures are several orders of magnitude larger than carbon fixed by crops having a similar height but, in agriculture's defense, forests contain carbon sequestered over many years

C. *Nutrient flows*

Using the crop nutrient tool and assuming that all aboveground biomass is harvested we can calculate the quantities of N, P and K contained in both the grain and the hay (Tables VIII-XI) for the row crops. The tables do not include grasses since we assume that they are consumed locally at the farm and thus require little fertilizer addition. Also not included is Nitrogen in soybeans, which is fixed by the rhizosphere, and soybean stover because during pod harvest the leaves have senesced thus making combined stover and pod harvest unpractical. These tables show that if hay is to be consistently harvested for biofuel production in addition to the grains, higher nutrient inflows will be required to maintain soil fertility. Also it should be noted that harvesting stover will also removes more micronutrients compared to harvesting just the grain and this can lead to field macronutrient deficiencies in the long term. These numbers show that even when only the grain is harvested modern intensive agriculture requires nutrients far in excess the of the natural ability of the ecosystem to fix nitrogen or provide phosphorus and potassium from the parent material through weathering.

D. *Economic Analysis*

Table XII shows that despite recent increased input costs, farm profitability has increased due to higher output prices. While our analysis takes into account highly volatile costs such as fuel, lube and fertilizer, it considers some costs such insurance and machine replacement costs as fixed. Economic

TABLE VI. NPP AND FIXED CARBON FOR THE CROPS GROWN IN HENRICO COUNTY

Year	Cropland Data Layer crop production		Quickstats crop production	
	NPP (Tons biomass)	*Fixed C (T)*	*NPP (Tons biomass)*	*Fixed C (T)*
2002	43825.9	19721.7	17472.9	7862.8
2008	36528.7	16437.9	NA	NA
2009	48245.1	21710.3	NA	NA
2010	41389.3	18625.2	NA	NA
2011	65282.0	29376.9	28059.6	12626.8
2012	41076.1	18484.2	NA	NA

TABLE VII. CARBON SEQUESTERED IF THE AGRICULTURAL LAND WAS FOREST IN THE STUDY AREA IN MT OF CARBON. ASSUMES DOMINANT STAND HEIGHT OF 1.52 M (5 FT)

County	Hardwood	Mixed
Albemarle	400136.3	418138.3
Charles City	87172.13	91093.98
Chesterfield	31320.22	32729.31
Henrico	69202.39	72315.79

TABLE VIII. ABOVEGROUND BIOMASS NUTRIENT QUANTITIES IN ABEMARLE COUNTY IN TONS

Year	Harvested parts except soy N			Aboveground not harvested		
	N	*P*	*K*	*N*	*P*	*K*
2002	510.8	98.3	116.9	306.8	227.5	551.3
2008	25.5	10.4	18.2	9.8	439.8	16.1
2009	61.3	15.9	23.5	19.9	493.9	34.1
2010	22.9	11.6	21.8	7.2	512.1	12.9
2011	74.5	21.4	32.3	24.7	501.7	38.5
2012	107.0	30.4	46.1	39.5	492.7	64.8

TABLE IX. ABOVEGROUND BIOMASS NUTRIENT QUANTITIES IN CHARLES CITY COUNTY IN TONS

Year	Harvested parts except soy N			Aboveground not harvested		
	N	*P*	*K*	*N*	*P*	*K*
2002	216.2	53.9	75.6	82.4	8.3	136.2
2008	451.0	118.7	172.9	180.9	18.2	306.4
2009	489.9	131.7	195.0	192.4	19.4	328.1
2010	487.3	123.5	174.8	179.6	18.1	295.2
2011	518.4	133.3	192.6	209.1	21.1	357.8
2012	576.0	141.2	196.3	218.7	22.1	363.2

TABLE X. ABOVEGROUND BIOMASS NUTRIENT QUANTITIES IN CHESTERFIELD COUNTY IN TONS

Year	Harvested parts except soy N			Aboveground not harvested		
	N	*P*	*K*	*N*	*P*	*K*
2002	26.1	7.8	12.2	10.6	1.1	17.5
2008	20.2	10.1	18.7	8.6	0.9	14.2
2009	13.6	8.3	16.0	4.5	0.5	6.9
2010	14.7	11.0	21.8	5.7	0.6	9.3
2011	12.4	5.3	9.3	4.0	0.4	6.1
2012	13.2	7.6	14.5	5.3	0.5	9.0

TABLE XI. ABOVEGROUND BIOMASS NUTRIENT QUANTITIES IN HENRICO COUNTY IN TONS

Year	Harvested parts except soy N			Aboveground not harvested		
	N	*P*	*K*	*N*	*P*	*K*
2002	102.3	28.9	43.4	36.5	3.7	60.0
2008	159.9	53.6	87.5	59.6	6.0	99.4
2009	182.6	81.6	148.7	65.8	6.7	118.5
2010	166.0	58.5	97.9	66.0	6.6	112.9
2011	373.1	85.8	113.1	125.2	12.7	201.6
2012	180.0	57.6	94.8	67.5	6.9	124.6

TABLE XII. PROFIT OR LOSS FOR STUDY AREA GRICULTURE

Year	Albemarle	Charles City	Chesterfield	Henrico
2002	-$344,508.57	$293,801.06	$29,747.21	$207,058.83
2008	$194,959.16	$2,203,134.45	$179,224.88	$1,158,896.45
2009	$169,087.35	$1,261,781.02	$142,211.05	$1,342,603.86
2010	$127,319.94	$4,168,962.71	$391,006.20	$1,999,834.50
2011	$975,579.37	$5,028,687.10	$228,091.24	$4,000,856.71
2012	$1,577,143.58	$7,105,996.59	$356,075.17	$2,659,882.77

farm output has been positive in the recent years which bode well for the economic survival of local farms and thus the continued provision of ESS from agro-ecosystems.

IV. DISCUSSION

Agriculture in the study area has the potential direct economic impact of over $11.5 million in 2012 but also the indirect benefits of NPP equal to 485,000 tons dry biomass that fixed 218,000 tons carbon but required an addition of 1200 tons of N, 750 tons of P and 900 tons of K to form grain and hay.

The Net Primary Production of the agro-ecosystems is similar to that of a fast growing temperate forest in the region [23] and potentially higher than of mature forests. However it also requires an input of nutrients also far in excess to what nature can provide. Carbon fixed every year is far inferior to what has been sequestered over the years in a tree stand of the same size having the same plant height. However the latter figure also includes soil organic carbon than can be far larger than biomass carbon. Also carbon sequestered in a forest can be released to the atmosphere in the event of a forest fire and thus can be less stable than it is usually assumed to be. In any case carbon that is part of the plant biomass is not in the atmosphere causing radiative forcing.

There is a movement to use biofuels to replace fossil fuels from transportation and power generation. The rationale is that biofuel carbon is not new carbon added to the atmosphere from geologic deposits. The use of biofuels has been critiqued because crops grown to provide them take land and water that can be used to grow food and that modern intensive agriculture also entails the emission of carbon to the atmosphere, albeit at a lower level than in the case of fossil fuels. In order to reconcile food and biofuel needs it has been proposed that marginal lands or crop residues should be used as biofuel feedstock. Our study finds that the study area includes a significant proportion of low productivity agricultural land that be successfully used to grow biofuels. Also the quantity of stover produced is quite significant. However harvesting of non-grain aboveground biomass will eventually require the addition of significantly increased quantities of nutrients.

A comparison of Quickstats and VALUES shows that there is for the most part an untapped productive potential in all 4 counties for most crops in the existent agricultural land. NASS policy not to release farm statistics in counties having few farmers so as to protect their confidentiality can lead to significant underestimation of NPP and stover estimations at scales finer than that of the state agricultural district [4],[5] and should be taken into account by future researchers.

Farm proceeds ought to reward farmers for the full benefits agro-ecosystems provide to society. In addition to fixed carbon which we evaluated in this study this also includes among others erosion control and water retention. Furthermore plant nutrients do not need to come from chemical fertilizer as in our analysis but can also be from organic byproducts such as biosolids, thus providing a valuable detoxification service. Our economic analysis has shown that the high farm gate prices of late have made farming quite profitable in the area. Unfortunately the only economic receipt for most farms is the price of agricultural products and it seems that the market price of farm products does not adequately capture the full value of ecosystem services provided by agricultural land. It should be noted though that markets for most ESS are still in their infancy.

In the future we intend to incorporate methodologies that capture other ecosystem services provided by agriculture such as water retention and soil erosivity. We hope that with our study we will inspire other researchers to further investigate ESS from agro-ecosystems and also to create better underlying models that can improve future studies.

ACKNOWLEDGMENT

We would like to thank Ann Darby, Pat Donovan and Dr. Wade Thomason for their help with this study.

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Identifying productive gaps and selecting area appropriate for conversion to small grain production in eastern Virginia and North Carolina

Introduction

Animal production is the largest contributor to the agricultural economy of Virginia and North Carolina. Current regional feed production does not meet the demand of animal feeding operations, which thus source a large portion of their feed grain from outside the region. This entails significant economic cost to the industry and environmental costs to society, including grain transportation costs, carbon emissions and net accumulation of nutrients as resulting manures are applied to agricultural soils. Our objective is to assess the potential to increase local feed grain production and evaluate impacts of these increases on the local environment. One option to increase feed production is through the intensification of production in existing crop fields, having farmers meet the yield that can realistically be grown under good management. Intensification should lead to increased but more efficient use of production inputs. Another other option is through extensification, the introduction of feed grain production into land of high productive capacity currently in other land uses. We first identify the characteristics of current agricultural production using land cover, soil and production data layers, and then identify highly productive areas currently not in agricultural use. While conversion to agriculture can increase provisioning ecosystem services, it can also affect other ecosystem services, especially soil and water retention at the local scale. We attempt to quantify these impacts using geospatial analysis tools to assess impacts of land change on ecosystem services at the regional scale.

Previous work addressing on the aspect of crop intensification, extensification and resulting tradeoffs between ecosystem services has been limited. Maxwell et al (2008) compared the cropland layer of the National Land Cover Database (NCLD) 2001 and Census of Agriculture (CoA) statistics of 2002 for 14 states in the Upper Midwest of the United States, also known as the Corn Belt. Unit of analysis was the county. The authors calculated the number of hectares of cropland in NLCD in each county and then compared this value with the figure given in the Census of Agriculture, which they considered to be the more accurate. The biggest differences among the datasets were found in counties that are along the edges of the study area having the lowest proportions of cropland. There were also significant differences in areas where the landscape is dominated by cropland and forest complexes such as most of Wisconsin, and parts of the non-irrigated plains such as the Dakotas where NLCD was not able to differentiate well dry cereal crops from prairie grasses.

Goslee (2011) compared CoA 1992 with NLCD 1992 and CoA 2002 with NLCD 2001 for all agricultural classes for 12 states in the Northeast. The unit of analysis was again the county. She tested several agricultural land cover classes in each county that had equivalent in the Census of Agriculture, interpolating where the latter did not offer data due to farmer confidentiality. There were differences between the datasets depending on the crop and the state. The NLCD tended to overestimate agricultural grassland and underestimate cropland with these two errors cancelling out, resulting in good estimates of the extent of broader agriculture.

Johnson (2013) developed a circa 2010 map of annually tilled land of the conterminous United States, based on aggregation of CDLs from 2008 to 2011, and compared it to the 2007 CoA. He found that compared to the 2007 CoA his layer systematically underestimated the extent of tilled land at the state level with the biggest discrepancies at Montana and North Dakota, where CDL has trouble differentiating unirrigated cereals from grass pasture. He added several more categories to his dataset as to compare it to NLCD 2006 and found that it systematic underestimated cropland, though to a much lesser extent than when comparing with the Census of Agriculture. He also notes that even though the extent of the layers match quite well, pixel location does not. For all states 81.7% of all pixels matched as non-cultivated in both datasets, 12.7% matched as cultivated, 3.4% were cultivated in NLCD but not in CDL and 2.1% were cultivated in CDL but not in NLCD.

Selection of the study area

In Virginia and North Carolina the core of agricultural land today is the Coastal Plain physiographic area, with intrusions in the Piedmont. Within both these regions agriculture is often the minority land cover, with most of the land being covered by forests. Our unit of analysis was the county since it allowed validation with statistics collected by the National Agricultural Statistical Service (USDA NASS 2014b). The study area included all counties within 160 km (100 miles) of existing feed mills in Waverly, Virginia and Rose Hill, North Carolina. We then added counties with rapid transportation options to those locations and a history of row crop production and farm services. The 2012 Cropland Data Layer (USDA NASS 2014a) shows the distribution of agricultural crops in the region, and served as the basis for refining our study area. Counties included are listed by NASS reporting district in Table 1, and shown in Figure 1, along with the location of the feed mills and the 160 km buffer.

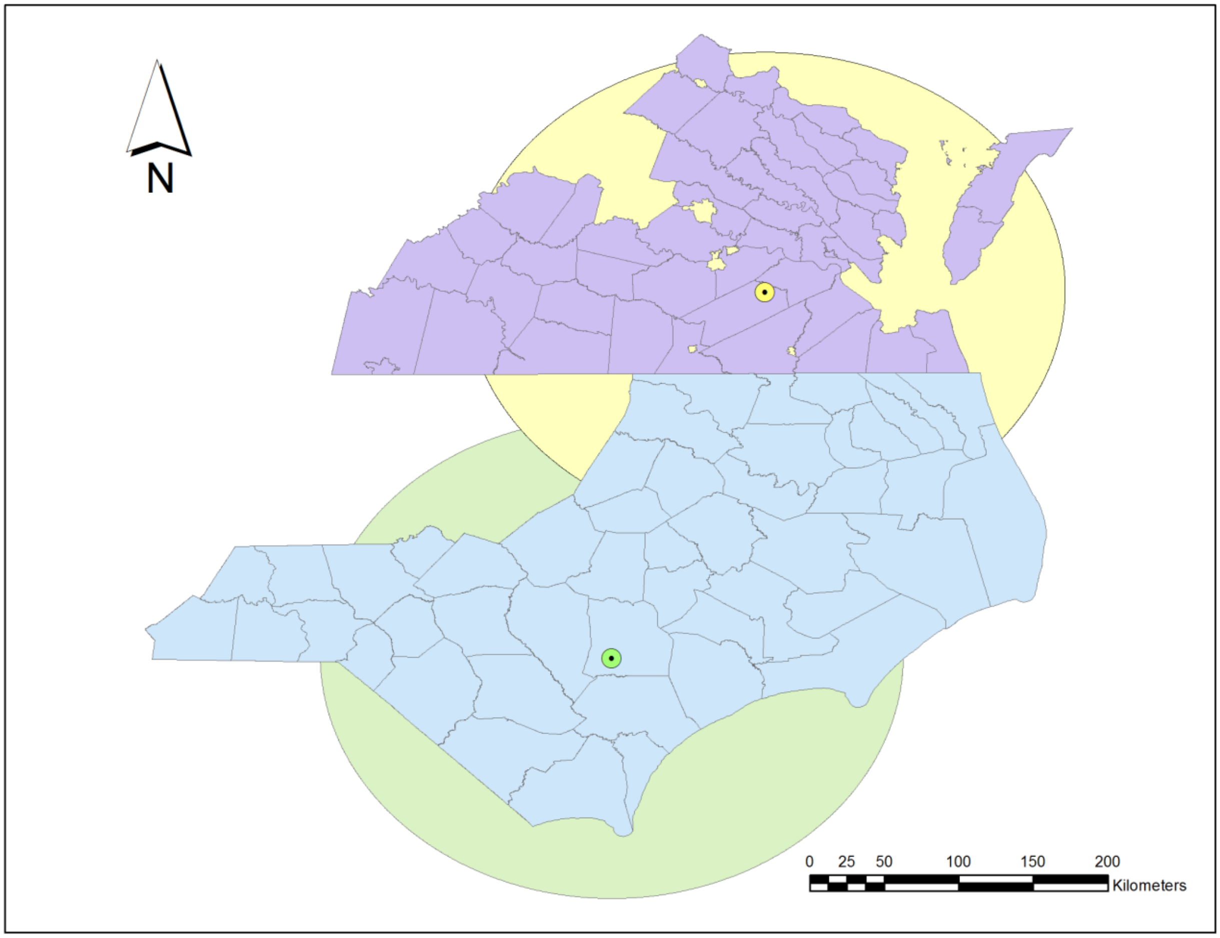

Figure 1. Location of feed mills, 160 km buffer and counties included in our study area

Datasets and tools used

The Virginia Agricultural Land Use Evaluation System (VALUES) is a tool created by Virginia Tech and the Virginia Cooperative Extension to help manage farmland in Virginia (Donohue et al 1994). Historically field scale nutrient recommendations were based on a yield goal where yield records were unavailable, but these seldom captured the variability in yield from field to field, and could be unrealistically lower or higher than the actual yields. A yield potential based on physical realities of the site (primarily soil properties) was needed. Counties using agricultural production value as the basis for taxation of lands in agricultural use also sought such information. Laws regulating use of nitrogen and phosphorus (especially as manure) now routinely use soil-based yield potentials to determine maximum application amounts where field-scale yield records are not available. A four year study began in 1989 to create a database of crop yields by soil series using information from variety trials, research plots, seed demonstrations and farmers who kept accurate records both in Virginia and other states with similar growing conditions. The soil series were placed into 43 management groups based on physiographic region and similar physical and chemical properties. Yield was then calculated based on statistical information derived from the trials. Productivity groups for each agronomic crop were comprised of soil management groups with similar agronomic performance for that crop, which are grouped for productivity, from group I (most productive) to V (least productive). Corn, sorghum and soybeans have productivity subgroups, with subgroup a being more productive than b. These groups are each assigned a numeric crop yield per subgroup. The end result is a database of over 900 soil series grouped for management recommendation and yield. The principle of yield calculated by VALUES is that it is a production yield that can be reached 3 out of 5 years under good management. It covers six agronomic, two silage, four hay crops and pasture. VALUES assumes all crops are non-irrigated but produced under good agronomic practice. It includes data both for standard or intensive production of wheat and barley, for full season or late planted (double cropped) soybeans. Yield unit is bushels per acre for agronomic crops, (short) tons per acre for hays and silage and Animal Units per acre for pasture. For some of the poorly drained soil series, VALUES has potential yield for both the presence and absence of artificial drainage. The most recent update of VALUES was in 2005 based on over 2700 data points (VADCR 2005).

Similar in scope but intended for North Carolina is the Realistic Yields Expectations database (RYE). It is a database of realistic yield under good management for the soils of North Carolina. It was created by North Carolina State University, the USDA Natural Resources Conservation Service (NRCS), North Carolina Department of Agriculture and Consumer Services and the North Carolina Division and Soil and Water Conservation. Yield collection began in 1999 and the database was most recently published in 2003. Its principal for yield is that it predicts what can be realistically achieved the best 3 of the 5 years under good management, generally the top 20% of growers. Yield figures for poorly drained soils have the implicit assumption that the soil is artificially drained. RYE assumes irrigation only for tobacco in Piedmont soils (North Carolina Nutrient Management Workgroup 2003); all other yields are for non irrigated conditions. It contains yield for a large number of crops, 10 agronomic, 4 silage and 13 hay crops. Yield unit for most grains is bu/ac with the exception of sorghum where it is given in cwt/ac (1 cwt = 100 lb). For cotton, tobacco and peanuts yield is given in lb/ac. There is no standardized weight for a bushel of triticale, we assume that it has the most common weight of 56 lb. For hays and silage yield unit is T/ac. For soybeans it has different figures for full season and late season soybeans, but for other crops it only has one yield value.

The Soil Survey Geographical Database (SSURGO) is a spatially distributed database of the soil series of the United States as mapped by the National Cooperative Soil Survey (Soil Survey Staff 2014) and maintained by NRCS. It is composed of updated digital versions of Order 2 NRCS soil survey maps and is available for most but not all of the United States. All the counties and independent cities selected for our study area were in the SSURGO database. The area mapped in SSURGO is broken into polygons of relatively homogeneous soil series with a minimum delineation size of approximately 0.4 ha. These soil survey units are often complexes of containing parts of several soil series. Soil surveys have taken place at different times for each county, resulting in differing accuracy. In 2012 a gridded version of SSURGO in a 10 m pixel raster format became available which we used along with the vector polygon version.

The USDA's National Agricultural Statistical Service (NASS) created the Cropland Data Layer (CDL) in the mid-1990’s. This land cover dataset which has an agricultural emphasis and coverage of the conterminous United States has been produced annually since 2008. A special characteristic of this layer is that NASS uses the confidential farmer declarations to the Farm Services Administration (FSA) to create a ground truth sample for classification and validation (Johnson & Mueller 2010). CDL 2010, 2011 and 2012 have a 30 meter pixel while CDL 2008 and 2009 have a 56 meter pixel. CDL, like most land cover products, is generally more accurate with classes that compose the majority of in each region. There is a trend of improving accuracy over the years that the dataset is produced. While the CDL is good at finding the general extent of agriculture, it suffers from significant errors of omission and commission (Kokkinidis et al in prep).

Another dataset originating from NASS is the Quickstats farm database website. Every quarter NASS conducts the Crops/Stocks (Agricultural Survey), and releases estimates of crop acreage, yields, total production, and quantities of grain and oilseeds stored on farms. The results are published in the March Prospective Plantings, June Acreage, September Small Grains Summary, quarterly Grain Stocks, monthly Crop Production, and the January Crop Production Summary, products known collectively as the Survey of Agriculture. This, along, with the Census of Agriculture which takes place every 5 years, is available from the Quickstats website (USDA NASS 2014b). The Quickstats website provides NASS-collected information at various scales: whole country, state, reporting district and county. To safeguard farmer confidentiality, NASS does not release crop information in cases where less than 500 acres are grown or where a small number of farmers are involved in the production of the crop in the reporting unit.

The National Elevation Dataset (NED) is the primary elevation data product of the USGS. It is a seamless dataset containing the best available raster elevation data of all US territories. NED data are distributed in geographic coordinates in units of decimal degrees and elevation values are in meters (USGS 2014). We used the 10 meter DEM product available for the study area, maintaining the same spatial resolution with gridded SSURGO.

The PRISM climate group is an ongoing effort to produce and disseminate detailed, high-quality spatial climate datasets, located at Oregon State University. It uses the Parameter-elevation Regressions on Independent Slopes Model (Daly et al 2008) to develop its spatial climate datasets. This data is available to the general public in a variety of formats, including the 1981-2010 30 year climate normals monthly and annual precipitation layers, which we used in this study.

The Integrated Valuation of Environmental Services and Tradeoffs (InVEST) suite is an open source collection of tools created by the Natural Capitals project, housed at Stanford University. It is an attempt to quantify a variety of ecosystem services provided by multiple ecosystems, terrestrial, freshwater and aquatic (Tallis et al 2013). Its intention is to help inform stakeholders about the tradeoffs regarding various decisions that modify the landscape, using models that incorporate the best available scientific knowledge about a subject. It is available as a standalone tool and as toolbox for ArcGIS, which we used.

Methods

Creating a yield geospatial database

We converted the VALUES handbook (VADCR 2005) to an MS Access database, associating each soil series name with its numeric yield for all available crops. Unfortunately the VALUES yield table only gives numbers for non-sloping land, though there is a generic yield reduction algorithm to correct for slope. In gridded SSURGO each unique identifier attribute MUKEY for every pixel (which corresponds to soil series) was associated with its soil mapping unit name. Using soil series/mapping unit names as the joining key factor, each MUKEY, and thus each pixel in gridded SSURGO, was associated with VALUES yield. Three soil series, Bojac, Glenelg and State had the same name but differed in yield depending on what region of Virginia they are located. We selected the higher productivity category which was also the more prevalent.

To account for slope effects on yield, slope was extracted from the NED 10 m DEM. Furthermore a Fall Line boundary was extracted from the NRCS Major Land Resource Areas vector dataset because slope yield reduction suggestions differ for the Coastal Plain and the Piedmont. To account for no-till practices, which are recognized to improve yield potentials on more highly sloping lands, two yield rasters were created for each crop, one for no till and one for conventional agriculture. The end product was a series of rasters, containing yield for different production methods for several major crops of Virginia. We call this database gridded VALUES (gVALUES). The specific cropping systems included in gridded VALUES are shown in Table 2. Figure 2 is a visualization of gVALUES for intensive corn.

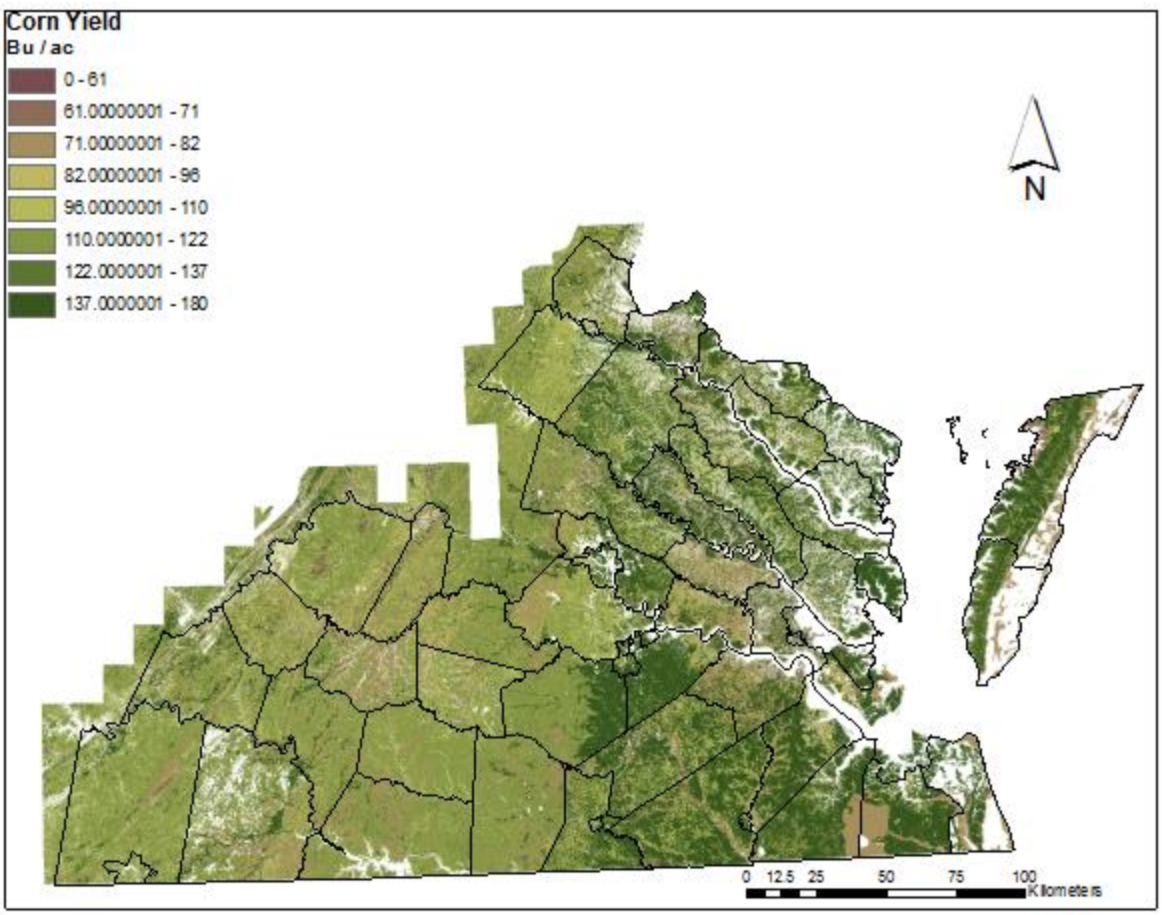

Figure 2. gVALUES intensive corn in bu/ac. Black borders indicate counties within the study area

RYE was obtained as an Access database containing yield by MUKEY. Each soil mapping unit in SSURGO, both in vector and raster formats, has a different MUKEY depending on the slope and county, even if it is of the same soil series. Thus there are multiple MUKEYs for the same soil series having the same slope category but corresponding to different counties and multiple MUKEYs for the same soil series in each county, depending on the slope. RYE has taken into account slope yield reduction but has the same yield correction factor for all the counties; all the physiographic regions have the same yield expectation for a particular soil series or complex. Furthermore, unlike VALUES, RYE does not include any correction factors for tillage method or production intensity. The RYE database was very easily joined with gridded SSURGO using MUKEY as the unique key identifier to create a geospatial version, which we call gridded RYE (gRYE). Table 3 shows crops in contained in gRYE, while figure 3 is an image of gRYE for corn in our study area.

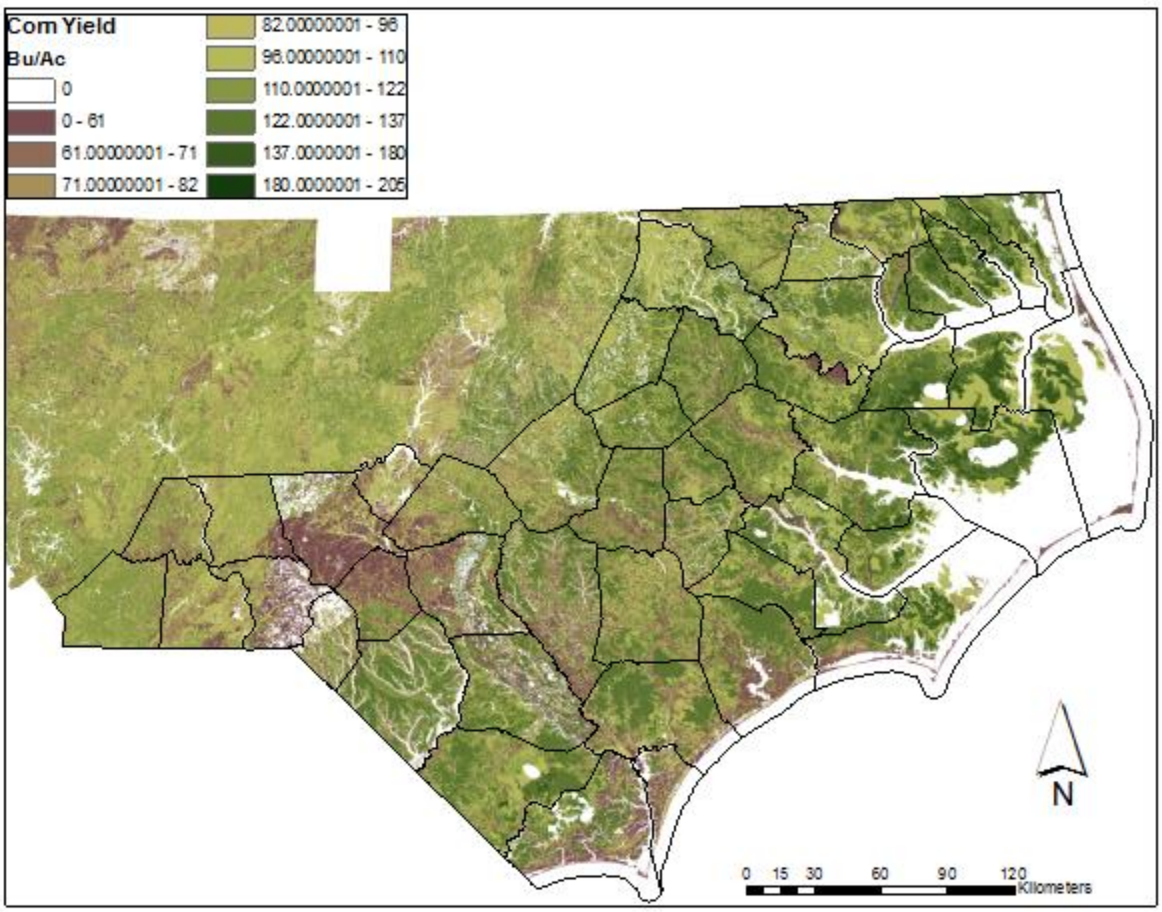

Figure 3. gRYE for corn in bu/ac. Black borders indicate counties within the study area

Calculating a potential yield gap

Produced Yields

We compared gVALUES and gRYE with crop area, production and yield information collected by NASS' Survey of Agriculture, as is available on the Quickstats website. Generally areas crop areas and yields are reported on a county-wide basis but also aggregated to the agricultural district, state and national level. However, NASS does not report data when low area (500 acres) or low numbers of farmers (5) in the reporting unit are involved and disclosure would reveal confidential information. The principle used while collecting information from Quickstats (labeled Produced Yields) was to use as large a spatial division as possible so as to minimize confidential information and error of omission, hence privilege was given to reporting district over the specific county. Some districts contain counties outside our study area, thus the reference framework of the NASS, the spatial location of the information extracted from Quickstats does not exactly match our study area for most of the crop/year combinations. If a significant part but not the entirety of an agricultural district was in the study area, we would collect information for the district and subtract the counties that did not belong to our study area. Since NASS reports at the county level only if the crop is grown at significant areas, we believe to have minimized this error of commission.

Predicted Yields

The CDL contains information on 111 crops and cropping systems of Virginia and North Carolina and 25 non-agricultural land cover categories. We extracted from the CDL 2008-2012 the spatial extent and distribution of the pixels corresponding to each crop contained in the gVALUES and gRYE databases. We reclassified the CDL into a crop/no-crop scheme for each specific crop, irrespective of the production system. For soybeans, we specifically extracted two layers for each state and year, one for full season soybeans and one for late season/double cropped soybeans. All the pixels in each crop layer were then multiplied with gVALUES and gRYE to create a rasterized map of realistic yields (labeled Predicted Yields) for each of the five years and for each of the crops.

Selection criteria to identify new land suitable for agriculture

Regional Extension and industry experts indicate high interest on expanding the area of winter wheat production. Wheat is a high quality grain that may be double cropped with soybean and sorghum, and all are more tolerant to short duration drought than corn is. Thus, we sought to identify new lands having above average productivity for wheat in both the Virginia and North Carolina component of our study area. We used a number of simple criteria, designed more to exclude land that is unsuitable or unrealistic to convert:

- Land Cover

Land cover to be converted must be identified as forest, pasture, idle cropland or barren land as defined and labeled in CDL 2012. Forested wetlands were not considered land suitable for conversion.

- Legal Status

The pixel must not be in a US census designated metropolitan statistical area, a federal or state park, a military camp, a tribal area or in a conservation easement allocated to forested land. Lands in conservation easements for agriculture (but not currently in agricultural use) were considered eligible for selection.

- Yield

In Virginia the soil beneath the pixel must be allocated in VALUES to a yield category II or better for wheat, thus have a wheat yield of 70 bu/ac or better. For North Carolina, where wheat yields are lower and there are no designated categories, we chose land where RYE wheat yield is above the approximate state average value of 55 bu/ac.

- Hydrologic Group

Many soils assigned poorly and somewhat poorly drained soils (hydrologic group D in SSURGO) in Virginia and North Carolina have been previously drained for agricultural use or as forest plantations. However SSURGO does not discriminate between undrained and artificially drained soils. We assume that group D soils that are currently farmed (according to CDL) have been artificially drained, and have assigned yield potentials appropriate for that condition. For purposes of extensification, however, it is possible new drainage of such soils would not be permitted. There are a large number of forest tracts, especially in North Carolina, on group D soils that were previously drained and could be converted to agriculture. However, no dataset is available that shows their location. We choose to exclude from consideration all soils that functionally belonged to the D hydrologic group, including all soils assigned to A/D, B/D, C/D and D hydrologic groups in SSURGO.

Calculating impacts of agricultural expansion

If land that selected with the criteria above is converted to agriculture, there would be significant impacts on the local ecosystems and the region. In particular we might expect significant differences in runoff retention and soil erosion from the converted area. We quantify these impacts though geospatial modelling of the runoff and erosion process described below in order to understand the tradeoffs between provisioning and other ecosystem services.

Runoff calculation

Ferguson Curve Number method

To calculate runoff we used two methodologies, the Ferguson extension of the SCS Curve Number method to the monthly domain and the Zhang adaptation of the Budyko curve method, which is used in InVEST. Ferguson (1996) proposed an empirical method to calculate direct runoff on a monthly basis for the contiguous United States, as an extension of the SCS Curve Number method. His purpose was to facilitate hydrologic condition comparisons due to land cover change. In devising his method he used precipitation and runoff values from six meteorological stations containing representing different climatic regions of the contiguous United States. He tested various empirical mathematical models to join direct precipitation from each rainfall event calculated using the SCS curve number method and monthly precipitation and found that best fit to his data is provided by the equation form:

$Q = a + bP/(S^k)$ if $a + bP/(S^k) > 0$, ELSE $Q=0$ (1)

For equation (1) Q is direct runoff, P is precipitation and S potential maximum retention after runoff begins, all in inches and a, b and k are constants that depend on the specific station. Ferguson also calculated average constants for the entire conterminous United States. He validated the formula calculating Q using the curve number method from each precipitation event and summing total Q for each month of the average year, and comparing this to the Q calculated by the formula for each month for each meteorological station. The method requires data for monthly precipitation and the curve number. It simplicity allows its implementation using geospatial tools. The curve number changes when land cover changes thus allowing us to model runoff before and after land cover change. The method does not take into account potential changes in precipitation due to land cover changes.

We used the 30 year normals PRISM monthly precipitation raster dataset for the study area as an input for precipitation. Soil hydrological groups for the SCS curve number method is one of the many soil attributes available in SSURGO. We added data fields to the polygon SSURGO attribute table so that for each soil mapping unit we can show what hydrologic group it belongs to, and thus what percentage of each mapping unit belongs to each hydrologic group. For groups having multiple components from multiple hydrologic groups we listed the percentage of each soil component that belongs to each group and created a composite curve number based on the relative weight of each component and on the land cover class, which was rounded to the nearest integer. We reclassified CDL into land cover groups having the same water retention characteristics (table 4) and derived curve numbers for each land cover class group based on the literature (NRCS 1986, McEnroe & Gonzalez 2003, Shrestha et al 2006, Sumaraw 2013). This simplified raster was then vectorized and spatially joined with polygon SSURGO through the intersect function. This was performed for both Virginia and North Carolina. We rounded each value to the nearest integer and rasterized the curve number layer for each state. Then we calculated S as per the curve number method:

$S = (1000/CN) – 10$ (2)

All units in equation (2) are inches. We used Ferguson's a, b and k values for Atlanta GA ($a = -0.161$, $b = 0.235$, $k = 0.64$) rather than the national average because Atlanta is the closest of the stations he studied and has the climate most similar to our study area. We input these values in equation (1) and calculated runoff on a monthly basis for land both in its CDL 2012 condition and what its condition after selected land was converted to agriculture. After calculating Q, we selected only the positive values from each month and created a new raster with runoff volume in m^3.

Budyko curve implementation

The Budyko curve is an empirical model that partitions precipitation into runoff and evapotranspiration depending on the climate of each region. It was derived by Budyko based on his observations of a large number of hydrologic basins, mostly in the Soviet Union. Zhang (2001) modified it introducing a seasonality factor. This method is implemented in InVEST (Tallis et al 2013). Water Yield Y(x) for each pixel of the landscape is equal to:

$Y(x) = (1- AET(x)/P(x))*P(x)$ (3)

In equation (3) AET is actual annual evapotranspitation and P is precipitation, in mm. AET(x)/P(x) is also called the evapotranspiration partition of the water balance and for vegetated classes it is equal to:

$AET(x)/P(x) = (1+\omega(x)R(x))/(1+\omega(x)R(x)+1/R(x))$ (4)

For equation (4) R(x) is the Budyko Dryness Index, defined as the ratio of potential evapotranspiration to precipitation (Budyko 1974) and is dimensionless. It is calculated as:

$R(x) = Kc*ETo/P(x)$ (5)

The new parameters of equation (5) are Kc and ETo. Kc is the dimensionless evapotranspiration coefficient of each land cover class, derived from FAO data given in the InVEST documentation. ETo is reference evapotranspiration in mm which was extracted from the FAO 10 arc minute Reference Evapotranspiration raster. ω(x) is a modified dimensionless ratio of plant accessible water storage to expected precipitation during the year, defined by Zhang (2001) as:

$\omega(x) = Z*AWC(x)/P(x)$ (6)

Factor Z is Zhang's dimensionless seasonality factor, representing annual rainfall distribution and depth. For areas with summer rains or equal distribution throughout the year Z is equal to 1, for areas where precipitation falls mostly in the winter Z=10. In our study area we took Z=2. AWC is the volumetric plant available water content, in mm. It is estimated as the product of the difference between field capacity and the permanent wilting point and the minimum of root restricting layer depth and vegetation rooting depth. It is the quantity of water that can be held and released in the soil for use by a plant. All of these parameters are available or can be calculated from gridded SSURGO. For non-vegetated classes AET is calculated as:

$AET(x) = Kc * ETo$ (7)

Compared to the Ferguson curve number method, the Budyko curve method has seen wider application. However it also required far greater quantities of information in order to calculate than the curve number method. Some of this information, such as root restricting soil layer in Duplin county NC and potential evapotranspiration on a sliver on the Chesapeake side of the Virginia's Eastern Shore was unavailable. In that case we left those values blank and tried to do our best with what the tool calculated. We also had to supply estimates for some other parameters based on our experience and supplementary information in the InVEST documentation. Once all the information was available each iteration of the calculation for annual water yield took 90 to 120 minutes. The Ferguson method is more empirical but required far less information which was easier to obtain. McEnroe and Gonzalez (2006) have assigned the curve number for each NLCD class; our contribution was to expand the lookup table to cover the extra classes that CDL has.

Erosion calculation

We used two methods and their combination to calculate erosion. The first method was the RUSLE 3d variation of the Universal Soil Loss Equation (Mitasova et al 1996). The second method was the Unit Stream Power - based Erosion Deposition (USPED) method (Mitasova et al 1999). Finally we also used area experiencing erosion as calculated by the USPED method as a mask input for erosion calculated by RUSLE 3d.

USLE implementation

USLE has been used since its introduction in the 1930's to calculate erosion worldwide. It states

E= R*K*L*S*C*P (8)

Its parameters are E, erosion, R, rainfall energy factor, K, soil erosivity factor, L, slope length, S, the slope steepness factor (L and S together are usually called in combination the LS slope length factor), C, the cover factor and P, the protective practices factor. USLE has seen several revisions and many geospatial implementations over the years. The units used originally are those of the imperial system although the equation has seen application using metric units. Among factors R and K have units, while LS, C and P are unitless. For this study we used imperial units when calculating erosion in (short) tons per acre and converted the final product to metric tons, due to K being available in imperial units ((ton*acre*hour)/(hundreds of acre*foot*tonf*inch)) in SSURGO. We calculated the rainfall energy R from annual precipitation using the Renard and Freimund (1994) equation for areas of the continental US having more than 850 mm of annual rainfall:

R-factor = 587.8 - 1.219P + 0.004105P^2 (9)

Factor R is calculated in metric units (Megajoule/(hectare*millimeter)) and P is precipitation in mm. To convert to imperial units ((foot*ton)/(acre*inch)) we divided by 17.02, creating thus an R raster based on the PRISM annual 30 year normals raster. K is available in gridded SSURGO, we thus used it to create a K raster using database joins in ArcGIS. C and P factors depend on land cover. We used values in table 5 to calculate C and P values from the 2012 CDL, based on values we found in the literature (Kroner and Cozie 1999, Franzmeier and Steinhardt 2009, Miller 2014, Wischmeier & Smith 1978, Vezina et al 2006, Kouli et al 2009). We are assuming that agriculture is practiced under conservation tillage, thus has a P value of 0.5 for single crops and 0.3 for double crops. When there is land cover change, it is C and P that change the calculated values of erosion as per the USLE. For LS we used the RUSLE 3d method (Mitasova et al 1996). In this variation of USLE, the LS factor is no longer slope length but rather the contributing area (number of pixels) draining into each eroded pixel. For this calculation we used the formula:

$LS = (m+1)([A/a_0]^m)*([\sin b/b_0]^n)$ (10)

Parameter A, in meters, is upslope contributing area per unit contour width, calculated using the slope accumulation tool in ArcGIS Hydrology. It is equal to:

A = [flow accumulation]*[pixel resolution] (11)

Following the suggestions of Mitasova, we used the 10 m NED DEM of our study area to calculate the A factor. Parameter b is the pixel slope, calculated from the NED DEM in degrees and converted to radians since ArcGIS assumes all trigonometric input is in radians. Parameters m and n are unitless parameters while a_0 = 22.1m is the length and b_0 = 0.09 = 9 % = 5.16 degrees is the slope of the standard USLE plot. It has been shown that the values of m=0.6, n=1.3 give results consistent with the RUSLE LS factor for slope lengths less than 100m and slope angles less 14 degrees (Moore and Wilson 1992), for slopes with negligible tangential curvature, thus they were used in this implementation. Mitasova warns that in order to calculate the LS factor using the RUSLE 3d method, we must exclude pixels with net soil deposition. Otherwise, even though there are zones of deposition, equation (10) will calculate excessive erosion values. Due to the very large extent of our study area, several of the pixels, corresponding to the hydrographic network, indeed had A values in the order of millions of meters. Unfortunately Mitasova does not propose a specific method to create such a mask. Our first approach, which we use as our first calculation method, is to limit the maximum slope length to 100 m or 10 pixels since this is the limit for which our m and n values refer to in Moore and Wilson (1992). Note that Moore and Wilson did not place a hard limit at 100 m or 14 degrees in their study; they were unable to find field studies with higher values for slope length and angle. Assuming that 10 pixels contribute to each side, this leads to a maximum contributing area of 40 pixels or 4000 m^2. We thus masked out all A values larger than 40 pixels.

USPED

USPED is a two dimensional model of the distribution of erosion and deposition where erosion is depended not only on rainfall detachment but also on sediment transportation capacity. If the sediment transportation capacity T of the pixel is not sufficient, there will be deposition rather than erosion. Transport capacity is calculated using the parameters of RUSLE 3d as:

$T = R * K * C * P * A^m *(\sin b)^n$ (12)

In this case though, the m and n value differ from those used in RUSLE 3d. There are two erosion options for the USPED method, prevailing sheet erosion, which we assumed was true in our study area, and prevailing rill erosion. For prevailing sheet erosion both are set equal to m=n=1. Furthermore in this method it is water that is being collected and transported; hence, unlike for RUSLE 3d, we initially placed no upper limit for A values. However there were several pixels for which the values were in the millions of tons per hectare, again corresponding to the hydrographic network. We could not find papers discussing proper values for the m and n factors in USPED but we decided to place a flow accumulation limit of 40 in our implementation of this method, analogous to what we placed in RUSLE 3d. Erosion and deposition are calculated as a divergence of T, equal to:

ED = d(T*cos a)/dx + d(T*/sin a)/dx (13)

For equation (13) a is the aspect of the DEM, in our case the NED. To calculate this divergence, we need to compute the aspect and slope of following parameters:

qsx = T*cos a (14)

qsy = T*sin a (15)

ED for prevailing sheet erosion is equal to:

ED = (cos(qsx_aspect)*tan(qsx_slope) + sin (qsy_aspect)*tan(qsy_slope))*10 (16)

Erosion takes place where ED < 0 and deposition where ED >0. We used this method to extract erosion areas, masking out locations where there is net deposition. ArcGIS has issues when calculating the aspect of flat areas; its output value for such areas is -1. Trigonometric parameters are defined for that number and can contribute to the propagation of error when calculating the divergence using equation (16). In our study area such flat areas turned out to be the water bodies, more specifically the center pixels of major rivers, the coastal waters and the open ocean. Since there is no soil erosion from the surface of the water bodies, these areas where also excluded from erosion.

Combination of RUSLE 3d and USPED

When an upper limit is placed for flow accumulation, as we did for our USPED implementation, we can expect some distortion in the location of erosion and deposition. If we calculate USPED without any sort of upper limit on its values, we can more accurately extract the locations in the landscape where erosion and deposition takes, even though the value of erosion and deposition for some pixels will be unrealistically large. Thus USPED with no limit can thus be used on its own as a mask of eroding pixels. Preliminary results with the RUSLE 3d raster having no flow accumulation limit showed that while the USPED mask did reduce the number of pixels with excessive erosion values, it did not eliminate them. The surviving excessive erosion pixels still had a disproportionate effect in the average erosion of entire counties. Hence we decided to use the USPED erosion mask on the RUSLE 3d implementation with a maximum flow accumulation.

Results

Intensification

Produced Yields and Predicted Yields for each crop were aggregated at the state level for the 2008-2012 seasons, and are listed by crop in tables 6-15. The most complete Produced Yields datasets available were those for corn, soybeans and wheat for both states. For Virginia the barley dataset is also complete as is for North Carolina the peanuts dataset. For most other crops a single year of Produced Yields is available at best. CDL had difficulty in finding the extent and distribution of minor crops grown in the study area, though it became more successful as time progressed. Furthermore if a crop increased suddenly in extent grown in the study area, it was possible that NASS was not able to record it in Quickstats. This appears to be the case for sorghum in North Carolina in 2012. Thus it is most prudent to compare the geospatial and survey datasets for the crops for which the most complete series are available, corn, wheat and soybeans in both states (which will be referred to as the three major crops), barley in Virginia and peanuts in North Carolina.

The extent of agriculture (Produced Yields) for these crops has values that generally follow what the area of each crop was according to CDL. We should note that Survey of Agriculture estimates reported at Quickstats for recent years in have been incorporating geospatial information collected in the course of creating the CDL. Produced Yield was consistently less than Predicted Yield for all crops, with the exception of peanuts in North Carolina. Out of 10 years of corn data (5 per state) only once was produced yield higher than predicted yield. For soybeans this happened 4 out of 10 years, never for wheat or barley and 4 out of 5 years for peanuts. For the minor crops, when there a Produced Yield is available, it is often at 50% or less of Predicted Yield. However for these crops there is rarely a match between area reported in the Produced Yields and Predicted Yields datasets. One of the two area value in the datasets being compared is probably deficient and it is also possible that this alone can lead to spatial and yield mismatch.

Predicted Yield is consistent across the years within each crop for all the crops, major and minor. While the extent of each crop planted fluctuates, it seems farmers select fields having similar production potential to those previously used to produce that particular crop. Produced Yield fluctuated every year, in part due to the weather conditions. When comparing the 5 year averages (tables 6-15), soybean Predicted Yield and Produced Yield in Virginia had the most similarity, with produced yield at 95.6% of predicted yield. Greatest deviation (and thus yield gap) among the complete datasets was for corn in Virginia, produced yield was only 60.3% of predicted yield. For the rest of the crops where there is a 5 year Produced Yield data, it ranges from 68.9% (barley in Virginia) to 83.9% (soybeans in North Carolina) of Predicted Yield. RYE Predicted Yield, for all crops except soybeans, is closer to Produced Yield than VALUES Predicted yield is to its Produced Yield. The average predicted VALUES corn yield for the Virginia study area corresponded to VALUES productivity class IIIa while for the other crops average predicted yields region wide corresponded to productivity class II or IIa. RYE does not categorize yield in discrete production groups.

Extensification

Using the criteria outlined above, there are considerable amounts of land having above average potential yield in both states that can be converted into grain production (table 16). Virginia has the largest potential; suitable land is equal to 156.1% of the sum of the 2012 crop production area of the 6 VALUES agronomic crops in the study area. For North Carolina suitable land is equal to 25.0% percent of the sum of the exiting extent of the 10 RYE agronomic crops. Figures 4 and 5 map this suitable land. In each state the spatial distribution of this suitable land differs by county (tables 15 and 16). In Virginia suitable land is located outside the major urban centers, often at a significant distance from the sea coast. While a few counties near the Chesapeake Bay and urban centers have small amounts of land suitable for conversion both in absolute and relative figures, most other counties possess a large amount of land suitable for conversion. The majority of counties, 40 out of 49, have over 10% of their land suitable for conversion. Only the city of Williamsburg lacks any land suitable for conversion. Most suitable land for conversion is located in Pittsylvania county as absolute area (132,871 ha) and in Dinwiddie County as percent of the county's extent (62.8%).

In North Carolina counties located near the coast and in the southern Piedmont have limited amount of suitable land. A significant proportion of the land in the coastal counties has soils belonging to hydrologic group D. Most suitable land for conversion appears in counties of the middle and upper Coastal Plain. In only 4 out of 48 counties is the percentage of suitable land over 10%. Minimum value of suitable land is at Hyde County with 9 ha and less than one tenth of a percent of the county's extent. Maximum value of suitable land is at Duplin county, site of the Rose Hill feed mill. The criteria have found that 30,068 ha of land are suitable for conversion, which correspond to 14.13% of the county's extent.

The quantity of wheat that can be produced in the suitable areas is also very considerable. For Virginia its potential production is over 15 times the predicted production or about 19 times the actual wheat production of 2012. In North Carolina it is at 150% of predicted or actual production for 2012 (they had a 99% match that particular year).

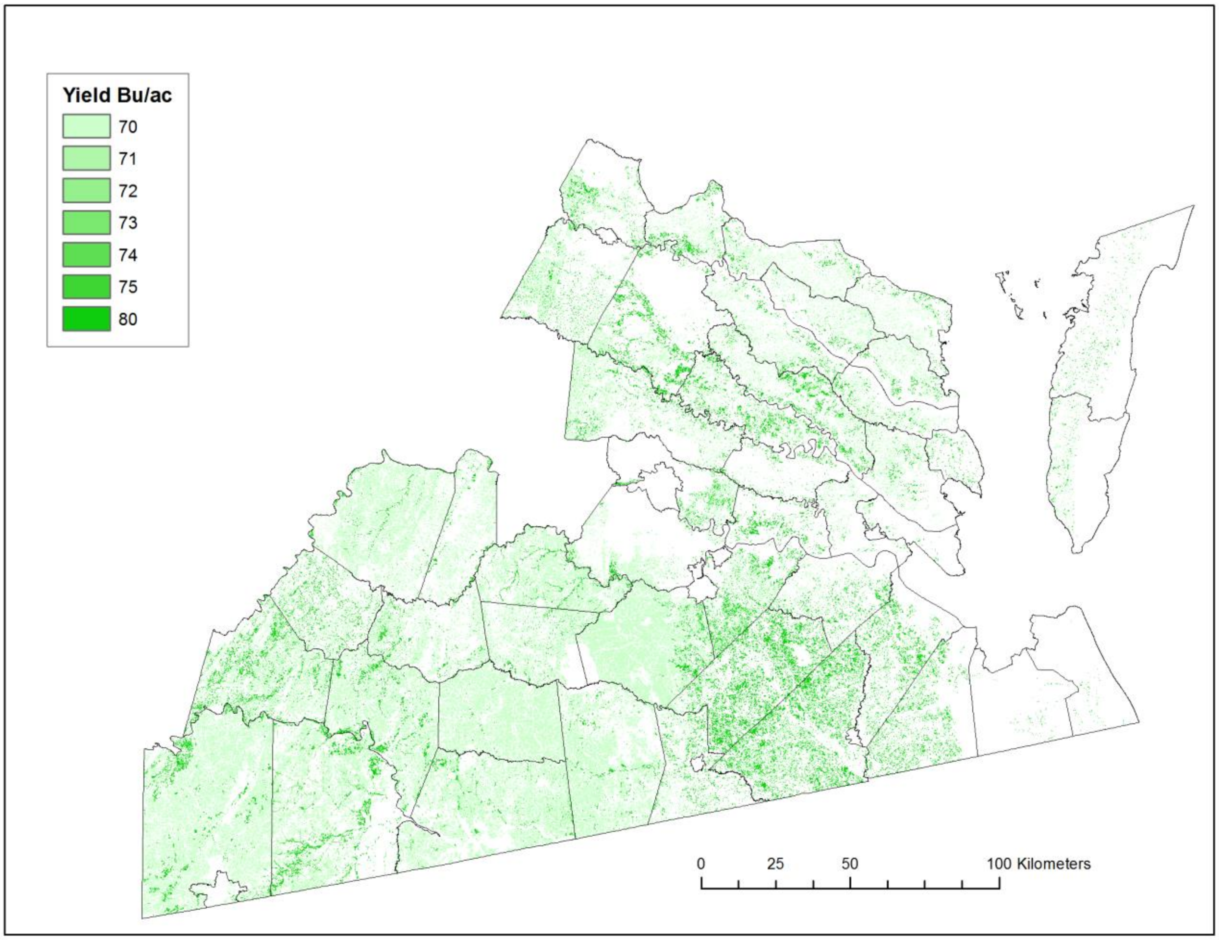

Figure 4. Land suitable for conversion to wheat production in the VA study area under our criteria

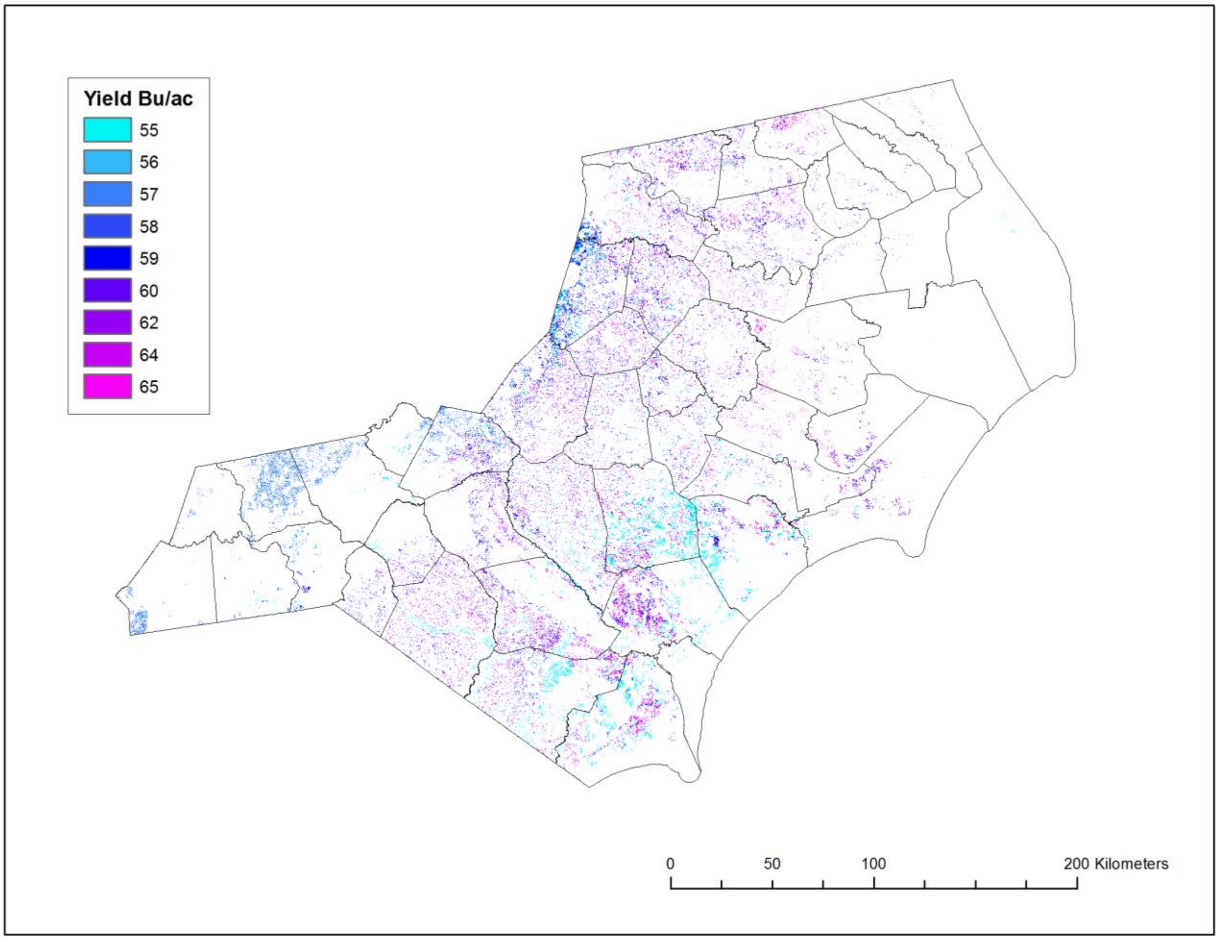

Figure 5. Land suitable for conversion to wheat production in the NC study area under our criteria

Impact on ecosystem services

Complete conversion of this suitable land, while increasing provisioning services, can also bring about several ecosystem disservices. We quantitatively modeled the potential impact of such land conversion on runoff and erosion, using 2012 as our base year (a.k.a. "before") and using the same methodology to calculate values after full conversion of such land to agriculture (a.k.a. "after"). We have calculated runoff (tables 19 and 20) and erosion (tables 21 - 26) both for the scale of the portion of the study area in each state and at the county / independent city level scale.

Runoff

At the state level calculated runoff volumes for Virginia before conversion was 33.2 million m^3 or 29.0 million m^3 according to the Ferguson and Zhang-Budyko methods respectively. This differs only in the order of 15 percent. After conversion it is modelled to increase to 38.4 million m^3 or 63.5 million m^3 for Ferguson and Zhang-Budyko respectively. In North Carolina modelled values for both methods before and after differ less than 8%. Conversion will increase runoff by 330,000 m^3 from 87.9 to 88.3 million m^3 according to the Ferguson method or by 9 million m^3 from 81.1 to 90.0 million m^3 according to Zhang-Budyko. At the county level there was significant divergence in values of calculated runoff for each method, although the same rank order in terms of volume is maintained for both methods. Both methods agree that there will be an increase in runoff and how the counties will be comparatively impacted. They disagree on what the absolute or relative quantities of that runoff increase will be. As always there are outliers. For example in Scotland county NC, runoff will decrease from 720,000 m^3 to 717,000 m^3 according to Ferguson, but will increase from 236,000 m^3 to 300,000 m^3 according to Zhang-Budyko. Only 3.48% of that county is suitable for conversion but the two methods treat this land differently; a significant amount of suitable land is idle cropland which for Ferguson is expected to have reduced runoff when it reenters agriculture but for Budyko, which treats it as grassland, is expected to have increased runoff. The counties experiencing the largest increase in runoff were those that also had the largest percent of area suitable for conversion. A comparison of the lists of the top 10 counties with suitable area (from table 17) and increased runoff (from table 19), 9 are common in both lists. They all are located in the Piedmont, west of Richmond. In North Carolina 6 of the 10 counties with the largest increase in runoff (from table 20) are also found in the list of the top 10 counties with the highest absolute area suitable for conversion (table 18). The counties with the highest increase in runoff are located in the Central Coastal Plain and Piedmont.

Erosion

RUSLE 3d with flow accumulation limit

On tables 21 and 22 are comparisons of mean and total erosion values in the 2012 land cover condition and after conversion for both states, reported county by county. In Virginia conversion of suitable land to agriculture leads to an increase of erosion by 11 times. In 16 counties erosion increases over 10 times, in no county is erosion decreased. RUSLE 3d shows erosion to increase in the city of Williamsburg despite the absence of pixels suitable for conversion, probably showing errors in implementation. Average erosion in the baseline condition as shown in CDL 2012 ("before") has its minimum value of 0.12 t/ha in the city of Williamsburg and in York county and maximum value of 2.86 t/ha in Westmoreland county. After conversion the minimum erosion rate will still be in the city of Williamsburg, but at 0.15 t/ha while maximum erosion will be at Lunenburg county with 24.58 t/ha. All areas that are seeing large increases in erosion are also seeing large increases in agriculture after conversion.

In North Carolina conversion of suitable land to agriculture leads to an increase of erosion by 1.77 times across all counties. Only in Montgomery county does erosion increases over 10 times; in Dare county erosion is decreased. Average erosion in the baseline land cover condition shown in CDL 2012 ("before") ranges from 0.07 t/ha in Dare county to 4.51 t/ha in Stanly county. After conversion the minimum erosion rate was found in Dare county and at 0.07 t/ha while maximum erosion was in Montgomery county with 9.06 t/ha. Increase in erosion is limited, as limited is the quantity of land found suitable for conversion in North Carolina.

RUSLE 3d with flow accumulation limit and USPED derived mask

On tables 23 and 24 are comparisons of mean and total erosion values in the 2012 land cover condition and after conversion for both states, reported county by county. In Virginia conversion of suitable land to agriculture leads to an increase of erosion by 5.12 times. In nine counties erosion increases over 10 times, in eight counties erosion is decreased. Among them is the city of Williamsburg which does not have any pixels suitable for conversion. Average erosion in the baseline condition as shown in CDL 2012 ("before") ranges from 0.08 t/ha in the city of Williamsburg and York county to 1.93 t/ha in Westmoreland county. After conversion minimum erosion rate is again found in the city of Williamsburg, but at 0.04 t/ha while maximum erosion will be at Lunenburg county with 10.96 t/ha. Again, all areas that are seeing large increases in erosion are also seeing large increases in agriculture after conversion.

In North Carolina conversion of suitable land to agriculture leads to a reduction of erosion to 0.76 times (that is approximately three quarters) its pre-conversion value. Maximum increase in erosion is in Montgomery county by 6.16 times. Erosion is increased in only eight counties, in the rest it is reduced. Average erosion in the baseline land cover condition as shown in CDL 2012 ("before") ranges from 0.06 t/ha in Dare county to 3.15 t/ha in Stanly county. After conversion minimum erosion rate will still be in Dare county but at 0.02 t/ha while maximum erosion will be at Montgomery county with 2.68 t/ha.

USPED erosion values

On tables 25 and 26 are comparisons of mean and total erosion values in the 2012 land cover condition and after conversion for both states, reported county by county. The values given are less than either implementation of RUSLE 3d, because areas with deposition were masked from this dataset and thus average is spread over an area that includes a large number of pixels having the value 0. In Virginia conversion of suitable land to agriculture leads to an increase of erosion by 10.37 times. In 16 counties erosion increases over 10 times, there is no county where erosion is decreased. The city of Williamsburg which does not have any pixels suitable for conversion sees an increase in erosion 1.17 times. Average erosion in the baseline condition as shown in CDL 2012 ("before") ranges from 0.01 t/ha in the city of Williamsburg and York county to 0.13 t/ha in Northumberland and Westmoreland counties. After conversion minimum erosion rate will still be in the city of Williamsburg, at 0.01 t/ha while maximum erosion will be at Lunenburg county with 1.58 t/ha.

In North Carolina conversion of suitable land to agriculture leads to an increase in erosion by 1.76 times. Maximum increase in erosion is in Montgomery county by 11.42 times. It is also the only county where erosion increases over 10 times. Erosion is reduced marginally (less than 1%) in Currituck and Dare counties. Average erosion in the baseline land cover condition as shown in CDL 2012 ("before") ranges from 0.01 t/ha in Dare and New Hanover counties to 0.22 t/ha in Stanly county. After conversion minimum erosion rate will still be in Dare county at 0.01 t/ha while maximum erosion will again be at Montgomery county with 0.4 t/ha.

Comparative erosion results

All three methods agree on the rank order among the counties of erosion before and after conversion but disagree on the intensity of the phenomenon and the intensity of change. RUSLE 3d and USPED expect erosion to increase in Virginia approximately 11 times; used in combination they expect an increase around 5 times. In North Carolina RUSLE 3d and USPED expect an increase in erosion over of 75%, their combination expects a reduction of 25%. A glance at the county results shows that the relative rank of the counties does not change. Lowest change in erosion takes place where suitable land is least available (the city of Williamsburg and Dare county); maximum change takes place where most conversion is expected. Values for total eroded soil weight and average erosion per county are not in agreement for any of the methods but there is consistent agreement on what is the relative impact of conversion.

Discussion

Intensification

Comparison between the Produced Yield and Predicted Yield tables shows that while both datasets generally agree over the area of each crop grown in the study area, the disagree on what yield and production ought to be. Our findings on the extent of agriculture as it compares between geospatial datasets and the Survey of Agriculture are consistent with the literature which compared though with the Census of Agriculture (Maxwell et 2008, Johnson 2013, Goslee 2011). A yield gap is present for most of the years and for most of the crops. Its value is differs among crops and the states, depending on both the specific climatic conditions of that year and the yield assumptions of each database. The very low ratio of Produced to Predicted yield for 2010 for all crops reflects the presence of a major drought that year. On the other hand the drought of 2012 had a smaller impact on the crop yield. This is supported by archival imagery for early September 2010 and 2012 from the US Drought Monitor archive (National Drought Mitigation Center 2014).

Out of 40 comparison pairs (Produced versus Predicted Yield) for crops with a significant times series, Produced Yield was higher only in 9 cases, 1 for corn, 4 for soybeans and 4 for peanuts. Had Produced Yield met Predicted Yield 3 out of 5 years, then it should have been higher for 24 out of 40 years. If in 2012 Produced Yield had reached Predicted Yield, over 280,000 tons of more corn and 75,000 tons of more wheat would have been produced in Virginia. Note that Drought Monitor shows that there was a limited drought in place which affected more North Carolina. North Carolina exceeded predicted yield expectation for all 3 major crops in 2012, as did Virginia for soybeans. This is but a small fraction of the over 6 million tons of wheat that can be expected after full scale extensification in Virginia alone, but it would only require improvements in farm management, not large scale modification of the landscape.

The geospatial yield databases allow yield modelling at the field level. While we selected to present comparative average yield at the state study area level, it is possible to extract Produced Yield at the county level for most of the counties in our study area. This, in combination with drought data from either the Drought Monitor or higher resolution data from GADMFS (Deng et al 2013) can help identify areas of consistently large yield gaps, so as to improve both farm yield and the soil yield databases.

The two soil yield databases (VALUES and RYE) give different potential yield for the same crop in the same soil series. This was due to many factors including actual differences in yield due to climate, homonymy of soil series, real pedological differences for the same series depending on location and data artifacts introduced during the creation of VALUES and RYE. One major difference between the two is that VALUES yield production groups have discrete categories that allows us to judge the relative quality of the soils where each crop is produced, which RYE does not. Since corn average potential crop yield belongs to a lower yield tier (IIIa) than for most other crops (II or IIa), it seems that it is more profitable to grow corn in soils of lesser quality than for the other crops. Future researchers could investigate crop profitability per yield group which can help inform decisions both on intensification and extensification.

Extensification

Our methodology showed that there is a considerable extent of highly productive land in both states, not currently in agriculture, that seems suitable for conversion. Complete conversion would lead to large scale landscape change though forests would still continue to be the dominant land cover in both states, decreasing from 39.25% to 28.78%[3] for the entire study area. Our objective was to assess the potential to increase local feed grain production and evaluate impacts of these increases on the local environment so that decision-makers can balance better assess tradeoffs. The positive impacts of conversion include the potential increase in provisioning services from extensification. Potential production from extensification is several times that achievable by intensification of production in current fields. Complete conversion would increase production by almost 8 million tons of wheat. Also if local agricultural production was to be increased, this would also bring an economic benefit to the area and strengthen the local community. The negative effects of extensification include increased runoff and erosion. We used a variety of models to quantify changes in both erosion and runoff, and the process allowed several observations for both the ecosystem services provided by agricultural land and the models used to quantify them.

Annual runoff would increase according to both of the methods used. Under full extensification the Ferguson method shows manageable runoff increases for both states, no more than 16% of the calculated baseline 2012 runoff for either of the states. Zhang-Budyko agrees for North Carolina, but forecasts doubling of runoff in Virginia. Even if we use the low estimates, considering the large extent of the study area, the change in runoff volume will have considerable impacts in the hydrology of the study area. While we did not model runoff change during extreme precipitation events, it is likely that improvements would be required on the flood protection structures of the local water bodies. Furthermore increased runoff should also impact the riverine flora and fauna. Note that even where the models agree at the state study area level, they show large variation at the county level. Both methods have strong empiricism and we are not aware of field studies in our study area that has use either of them to compare actual impact of land cover change in runoff. Furthermore there were a variety of assumptions in the input data of both methods; it is likely that several of those are false. More detailed studies that incorporate expert opinion and historical or field collected data are needed to better understand both changes in runoff and the modelling methods used to calculate them.

Erosion proved even more difficult to model geospatially. Comparison of the erosion models we used showcased several limitations of our implementation. We were not able to properly treat pixels with a large flow accumulation value, thus we were forced to introduce arbitrary limitations. In our models conversion from forest to agriculture can increase erosion by up to 20.000 times for a given field due to changes to C and P alone. However it can also bring more subtle changes to transportation capacity T,

[3] The definition of forests used for these numbers excludes forested wetlands

thus changing the location of erosion and deposition areas. When erosion C and P factors increased, so did T. Since USPED calculates erosion as a divergence, in locations where an agricultural pixel meets a forest pixel a buffer is formed at the edge of the agricultural field where USPED assumes deposition. Before erosion, in the presence of continuous forests no such buffer would form. We assumed conservation tillage and did not take into account the presence of erosion reducing structures, such as riparian buffers. The exclusion of hydrologic group D soils had the unforeseen benefit of excluding areas located among stream banks.

The methods disagree on what the average and total erosion value are, before and after conversion. Unfortunately field measurements to validate erosion calculations are lacking. Highest erosion values are found using RUSLE 3d with flow accumulation limitation only while the lowest are found with USPED used alone. Since the flow accumulation limitation of 40 pixels does not completely mask the areas of deposition, our opinion is that RUSLE 3d overestimates erosion values. On the other hand USPED calculated county and state average values by dividing the sum of a limited number of eroded pixel with a large number of pixels, most of which were not eroded. Our opinion is that it underestimates average county erosion. The combination of RUSLE 3d and USPED modelled erosion values that were between what was given by the other two methods. However it produced an unrealistic result for most of North Carolina where it predicts that erosion after conversion will be reduced. The changes in erosion in the city of Williamsburg despite the lack of suitable land and thus conversion are difficult to explain rationally and thus show that either the calculations were unrealistically set up, there were limitations in the erosion methods used or a combination of both reasons. Different erosion values in USPED despite lack of land cover change inside a small political unit are within reason since that method calculates landscape changes in the distribution of erosion. Changes in the divergence of T due to land cover change modify erosion over the entire area. RUSLE 3d though should have produced the same values for before and after conversion in Williamsburg. One possible reason is that a different projection system was used for the raster layers with the RUSLE 3d parameters that were used to calculate erosion before and after conversion.

A possible reason for the discrepancies in erosion values is the large geospatial scale used in this work. USLE is rarely implemented in for an area larger than the 8 digit HUC hydrologic units and USPED has never been experimentally validated (Mitasova and Mitas 1999), though Liu et al (2007) used it at Fort Benning GA and found it “useful”. Note that Fort Benning is far smaller in extent and more homogeneous than our study area. Perhaps there exists a maximum scale for the implementation of either of our methodology, which will not require the use of arbitrary limitations on flow accumulation. For future work we suggest working at a smaller spatial scale than the one used and the incorporation of field measurements of erosion.

While the methodologies used disagree on what the impact of conversion is on erosion, they agree of what is the rank order of relative impact among the counties of our study area. Counties with the largest increase in erosion tend to be concentrated in the Piedmont and the Atlantic coast. The Piedmont combines large tracks of suitable land for conversion with a significant amount of moderate sloping areas. In the Atlantic coast there is very large flow accumulation in the DEM, which led to very high LS values despite our efforts to mask them out. In Virginia counties with large quantities of land suitable to agriculture were also counties with large increases in modelled erosion. It seems that in Virginia the tradeoff between provisioning services and regulating services was more pronounced. In North Carolina limitations of our erosion model mean that the relationship was not so each to comprehend.

As the next step we propose further investigations at local scales to identify discrepancies and improve our models. Furthermore local scale investigations are easier to validate and verify. The models show that there is large spatial variability in the tradeoff between extensification of wheat production and runoff and erosion. We would suggest that future investigations commence in location where this tradeoff appears to be minimized.

Conclusion

The objective of this research was to investigate if and to what extent grain production might be increased in the region and the implication on associated ecosystem services. We used two approaches; one was intensification of current production, that is increase in Produced Yield so as to meet Potential Yield derived from soil yield databases. The other was extensification, selection and conversion of suitable land in other uses to agricultural production. Geospatial modelling shows that Produced Yield is significantly lower for most crops than Predicted Yield for most of the crops and years. While some of the yield gap is due to climatic conditions, part can be mitigated through the adaptation of improved management practices.

There is significant potential for extensification in the study area. In Virginia this land is equal to 150% of what is currently in production, in North Carolina 25%. Future work may address the question of why this land, if as productive as our models show, is not in agricultural use. Our models predict that extensification will entails significant environmental consequences. Runoff and erosion are expected to increase for most of the study area. Runoff will either increase by 16% or double in Virginia, depending on the model. In North Carolina it also is expected to increase but by no more than 11% at the state level. Erosion is modelled to increase either 5 or 11 times Virginia, and is predicted to be reduced by 25% or increase by little over 75% in North Carolina, depending on the model. Furthermore it seems that, at least for Virginia, as the proportion and quantity of land suitable is increased, so does the scope of ecosystem disservices.

Our models are but a first approach, to give a broad image of the potential for increased agricultural production. For large areas such as our study area, there are considerations that require adaptation of the models we have used which we were not able to identify, let alone mitigate. Our work should be followed up by local scale studies to identify areas, preferably in areas where the positive effects of conversion would outnumber the negative, using improved models and data. It was outside the scope of this study to calculate the economic and environmental impact brought by the current system of shipping grain to the study area, so as to compare it with the impacts of intensification and extensification. The choice on what is the preferred condition of the local landscape is up to the local communities to make, balancing what the perceived advantages of each condition are. We hope that through our work we have helped inform this choice.

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Tables

State	NASS Reporting District	County
Virginia	Northern	Stafford
	Central	Amelia
		Appomattox
		Buckingham

		Campbell
		Caroline
		Chesterfield
		Cumberland
		Greene
		Hanover
		Henrico
		Prince Edward
		Spotsylvania
	Southern	Charlotte
		Halifax
		Lunenburg
		Nottoway
		Pittsylvania
	Eastern (entire)	Accomack
		Charles City
		Essex
		Gloucester
		James City
		King and Queen
		King George
		King William
		Lancaster
		Mathews
		Middlesex
		New Kent
		Northampton
		Northumberland
		Richmond county
		Westmoreland
		York
	Southeastern (entire)	Brunswick
		Chesapeake City
		Dinwiddie
		Greensville
		Isle of Wight
		Mecklenburg
		Prince George
		Southampton
		Suffolk City
		Surry
		Sussex
		Virginia Beach City
North Carolina	Northern Coastal (entire)	Bertie
		Camden
		Chowan

		Currituck
		Dare
		Edgecombe
		Gates
		Halifax
		Hertford
		Martin
		Nash
		Northampton
		Pasquotank
		Perquimans
		Tyrrell
		Washington
	Central Coastal (entire)	Beaufort
		Carteret
		Craven
		Greene
		Hyde
		Johnston
		Jones
		Lenoir
		Pamlico
		Pitt
		Wayne
		Wilson
	Southern Coastal	Bladen
		Brunswick
		Columbus
		Cumberland
		Duplin
		Harnett
		Hoke
		New Hanover
		Onslow
		Pender
		Robeson
		Sampson
		Scotland
	Central Piedmont	Lee
	Southern Piedmont	Union
		Stanly
		Anson
		Montgomery
		Richmond
		Moore

Table 1. List of counties and independent cities in the study area per NASS agricultural reporting district

Crop	Method 1	Method 2
Intensive Corn	No till	Conventional Tillage
Intensive Wheat	No till	Conventional Tillage
Intensive Barley	No till	Conventional Tillage
Early Soybean	No till	Conventional Tillage
Late Soybeans	No till	Conventional Tillage
Grain Sorghum	No till	Conventional Tillage
Oats	No till	Conventional Tillage

Table 2. Crops and Systems in gVALUES

Crop
Barley
Corn
Cotton
Oats
Peanuts
Rye
Sorghum
Soybeans, early and full season
Triticale
Wheat

Table 3. Crops in gRYE

CDL class	Description	Type	Group A	Group B	Group C	Group D
0	No Data	NoData	NoData	NoData	NoData	NoData
1	Corn	Single row crop	67	78	85	89
2	Cotton	Single row crop	67	78	85	89
3	Rice	Small Grain	63	75	83	87
4	Sorghum	Small Grain	63	75	83	87
5	Soybeans	Single row crop	67	78	85	89
6	Sunflowers	Single row crop	67	78	85	89
10	Peanuts	Single row crop	67	78	85	89
11	Tobacco	Single row crop	67	78	85	89
12	Sweet Corn	Single row crop	67	78	85	89
13	Popcorn or Ornamental Corn	Single row crop	67	78	85	89
14	Mint	Single row crop	67	78	85	89
21	Barley	Small Grain	63	75	83	87
22	Durum Wheat	Small Grain	63	75	83	87
23	Spring Wheat	Small Grain	63	75	83	87
24	Winter Wheat	Small Grain	63	75	83	87
25	Other Small Grains	Small Grain	63	75	83	87
26	Winter Wheat/Soybeans Double Cropped	Double crop	64	75	82	86
27	Rye	Small Grain	63	75	83	87
28	Oats	Small Grain	63	75	83	87

29	Millet	Small Grain	63	75	83	87
30	Speltz	Small Grain	63	75	83	87
31	Canola	Single row crop	67	78	85	89
32	Flaxseed	Single row crop	67	78	85	89
33	Safflower	Single row crop	67	78	85	89
34	Rape Seed	Single row crop	67	78	85	89
35	Mustard	Single row crop	67	78	85	89
36	Alfalfa	Pasture/Hay	49	69	79	84
37	Other Hays	Pasture/Hay	49	69	79	84
38	Camelina	Pasture/Hay	49	69	79	84
39	Buckwheat	Small Grain	63	75	83	87
41	Sugarbeets	Single row crop	67	78	85	89
42	Dry Beans	Single row crop	67	78	85	89
43	Potatoes	Single row crop	67	78	85	89
44	Other Crops	Single row crop	67	78	85	89
45	Sugarcane	Single row crop	67	78	85	89
46	Sweet Potatoes	Single row crop	67	78	85	89
47	Misc. Vegetables and Fruits	Single row crop	67	78	85	89
48	Watermelon	Single row crop	67	78	85	89
49	Onions	Single row crop	67	78	85	89
50	Cucumber/Pickles	Single row crop	67	78	85	89
51	Chick Peas	Single row crop	67	78	85	89
52	Lentils	Single row crop	67	78	85	89
53	Peas	Single row crop	67	78	85	89
56	Hops	Single row crop	67	78	85	89
57	Herbs	Single row crop	67	78	85	89
58	Clover/Wildflowers	Legume	58	72	81	85
59	Seed/Sod Grass	Pasture/Hay	49	69	79	84
60	Switchgrass	Pasture/Hay	49	69	79	84
61	Fallow/Idle Cropland	Fallow	74	83	88	90
62	Grass/Pasture/Non-agricultural	Pasture/Hay	49	69	79	84
63	Woodland	Forest	36	60	73	90
64	Shrubland	Shrubland	35	56	70	77
65	Barren	Barren	77	86	91	94
66	Cherry Orchards	Transitional	43	65	76	82
67	Peaches	Transitional	43	65	76	82
68	Apples	Transitional	43	65	76	82
69	Grapes	Transitional	43	65	76	82
70	Christmas Trees	Transitional	43	65	76	82
71	Other Tree Crops	Transitional	43	65	76	82
72	Citrus	Transitional	43	65	76	82
74	Pecans	Transitional	43	65	76	82
75	Almonds	Transitional	43	65	76	82
76	Walnuts	Transitional	43	65	76	82

77	Pears	Transitional	43	65	76	82
81	Clouds	NoData	100	100	100	100
82	Urban/Developed	High Residential	61	75	83	87
83	Water	Water	100	100	100	100
87	Wetlands	Herbaceous Wetland	49	69	79	84
88	Nonag/Undefined	Barren	77	86	91	94
92	Aquaculture	Water	100	100	100	100
111	Open Water	Water	100	100	100	100
112	Perennial Ice, Snow	Water	100	100	100	100
121	Developed/Open Space	Urban Grasses	39	61	74	80
122	Developed/Low Intensity	Low Residential	57	72	81	86
123	Developed/Medium Intensity	Medium Residential	59	74	82	87
124	Developed/High Intensity	High Residential	61	75	83	87
131	Barren	Barren	77	86	91	94
141	Deciduous Forest	Forest	36	60	73	90
142	Evergreen Forest	Forest	36	60	73	90
143	Mixed Forest	Forest	36	60	73	90
152	Shrubland	Shrubland	35	56	70	77
171	Grassland Herbaceous	Grassland Herbaceous	49	69	79	84
181	Pasture/Hay	Pasture/Hay	49	69	79	84
182	Cultivated Crop	Single row crop	67	78	85	89
190	Woody Wetlands	Woody Wetland	36	60	73	90
195	Herbaceous Wetlands	Herbaceous Wetland	49	69	79	84
204	Pistachios	Single row crop	67	78	85	89
205	Triticale	Small Grain	63	75	83	87
206	Carrots	Single row crop	67	78	85	89
207	Asparagus	Single row crop	67	78	85	89
208	Garlic	Single row crop	67	78	85	89
209	Cantaloupes	Single row crop	67	78	85	89
210	Prunes	Single row crop	67	78	85	89
211	Olives	Transitional	43	65	76	82
212	Oranges	Transitional	43	65	76	82
213	Honeydew Melons	Single row crop	67	78	85	89
214	Broccoli	Single row crop	67	78	85	89
216	Peppers	Single row crop	67	78	85	89
217	Pomegranates	Transitional	43	65	76	82
218	Nectarines	Transitional	43	65	76	82
219	Greens	Single row crop	67	78	85	89
220	Plums	Transitional	43	65	76	82
221	Strawberries	Single row crop	67	78	85	89
222	Squash	Single row crop	67	78	85	89
223	Apricots	Transitional	43	65	76	82

224	Vetch	Legume	58	72	81	85
225	Dbl Crop WinWht/Corn	Double crop	64	75	82	86
226	Dbl Crop Oats/Corn	Double crop	64	75	82	86
227	Lettuce	Single row crop	67	78	85	89
229	Pumpkins	Single row crop	67	78	85	89
230	Dbl Crop Lettuce/Durum Wht	Double crop	64	75	82	86
231	Dbl Crop Lettuce/Cantaloupe	Double crop	64	75	82	86
232	Dbl Crop Lettuce/Cotton	Double crop	64	75	82	86
233	Dbl Crop Lettuce/Barley	Double crop	64	75	82	86
234	Dbl Crop Durum Wht/Sorghum	Double crop	64	75	82	86
235	Dbl Crop Barley/Sorghum	Double crop	64	75	82	86
236	Dbl Crop WinWht/Sorghum	Double crop	64	75	82	86
237	Dbl Crop Barley/Corn	Double crop	64	75	82	86
238	Dbl Crop WinWht/Cotton	Double crop	64	75	82	86
239	Dbl Crop Soybeans/Cotton	Double crop	64	75	82	86
240	Dbl Crop Soybeans/Oats	Double crop	64	75	82	86
241	Dbl Crop Corn/Soybeans	Double crop	64	75	82	86
242	Blueberries	Transitional	43	65	76	82
243	Cabbage	Single row crop	67	78	85	89
244	Cauliflower	Single row crop	67	78	85	89
245	Celery	Single row crop	67	78	85	89
246	Radishes	Single row crop	67	78	85	89
247	Turnips	Single row crop	67	78	85	89
248	Eggplants	Single row crop	67	78	85	89
249	Gourds	Single row crop	67	78	85	89
250	Cranberries	Transitional	43	65	76	82
254	Dbl Crop Barley/Soybeans	Double crop	64	75	82	86

Table 4. Curve numbers and simplified group for all CDL land cover classes

CDL code	Crop	C	P
1 to 25	Single crop	0.35	0.5
26	Double crop	0.3	0.3
27 - 35	Single crop	0.35	0.5
36 - 37	Grass	0.02	0.03
38-58	Single crop	0.35	0.5
59 - 62	Grass	0.02	0.03
63	Forest	0.003	0.003
64	Shrub	0.05	0.003
65	Barren	0.8	1
66 - 68	Cult Trees	0.1	0.3
69	Vineyards	0.3	0.3
70 -77	Cult Trees	0.1	0.3

81	Clouds	NoData	NoData
82	Urban	0.01	0.02
83	Water	NoData	NoData
87	Wetland	0.02	0.02
88 - 111		NoData	NoData
121 -122	Low Urban	0.02	0.02
123- 124	High Urban	0.01	0.02
131	Barren	0.8	1
141 - 143	Forest	0.003	0.003
152	Shrub	0.05	0.003
171 - 181	Grass	0.02	0.03
190 - 195	Wetland	0.02	0.02
204 -229	Single crop	0.35	0.5
230 -241	Double crop	0.3	0.3
242 - 250	Single crop	0.35	0.5
254	Double crop	0.3	0.3

Table 5. C and P factors

Virginia	**Produced**				**Predicted**				**Yield Ratio**
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	122134	705957	5.78	92.09	136871	1176056	8.59	136.893	0.67
2009	124724	853434	6.84	109.01	127532	1097749	8.61	137.1352	0.79
2010	129904	342217	2.63	41.97	156540	1331142	8.50	135.4761	0.31
2011	129257	795710	6.16	98.08	103443	893227	8.63	137.5702	0.71
2012	131361	590120	4.49	71.57	111866	965119	8.63	137.4506	0.52
5 year average			*5.18*	*82.54*			*8.59*	*136.91*	*0.62*
North Carolina	**Produced**				**Predicted**				
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	310192	1452160	4.68	74.58	440335	3080172	7.00	111.4438	0.67
2009	299710	2139216	7.14	113.71	363514	2659845	7.32	116.5733	0.98
2010	311446	1747537	5.61	89.39	361362	2650696	7.34	116.8641	0.76
2011	294692	1445804	4.91	78.16	341171	2506880	7.35	117.0647	0.67
2012	283199	2117327	7.48	119.11	312102	2329867	7.47	118.932	1.00
5 year average			*5.96*	*94.99*			*7.29*	*116.18*	*0.82*

Table 6. Corn area, production and yield in the VA and NC study area, according to Quickstats and geospatial data and methods

Virginia	**Produced**				**Predicted**				**Yield Ratio**
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	213148	444482	2.09	31.01	239635	563929	2.35	34.99	0.89
2009	213472	519806	2.44	36.21	273947	653183	2.38	35.45	1.02
2010	205257	326505	1.59	23.65	262691	638243	2.43	36.13	0.65
2011	200765	526076	2.62	38.96	208438	488316	2.34	34.84	1.12
2012	213027	576567	2.71	40.25	218318	514343	2.36	35.03	1.15
5 year average			*2.29*	*34.02*			*2.37*	*35.29*	*0.96*
North Carolina	**Produced**				**Predicted**				

Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	594766	1319083	2.22	32.98	617850	1575053	2.55	37.91	0.87
2009	637339	1445918	2.27	33.73	750181	1952660	2.60	38.70	0.87
2010	547621	947999	1.73	25.74	657617	1735162	2.64	39.23	0.66
2011	466522	937712	2.01	29.89	518602	1331266	2.57	38.17	0.78
2012	544747	1423563	2.61	38.86	610490	1560880	2.56	38.02	1.02
5 year average			*2.17*	*32.24*			*2.58*	*38.41*	*0.84*

Table 7. Soybean area, production and yield in the VA and NC study area, according to Quickstats and geospatial data and methods

Virginia	**Produced**				**Predicted**				**Yield Ratio**
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	113150	499011	4.41	65.58	109281	559363	5.12	76.11	0.86
2009	90771	308611	3.40	50.56	95177	484109	5.09	75.63	0.67
2010	65195	196303	3.01	44.77	65807	334966	5.09	75.69	0.59
2011	98298	448833	4.57	67.90	82721	421266	5.09	75.73	0.90
2012	103114	397254	3.85	57.29	86155	409838	4.76	70.73	0.81
5 year average			*3.85*	*57.22*			*5.03*	*74.78*	*0.77*
North Carolina	**Produced**				**Predicted**				
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	277898	932867	3.36	49.92	271431	1067455	3.93	58.48	0.85
2009	235972	650397	2.76	40.98	208486	817894	3.92	58.33	0.70
2010	167783	265977	1.59	23.57	136974	532567	3.89	57.81	0.41
2011	232897	879933	3.78	56.18	213129	839079	3.94	58.54	0.96
2012	277250	1004526	3.62	53.88	274882	1005811	3.66	54.41	0.99
5 year average			*3.02*	*44.91*			*3.87*	*57.52*	*0.78*

Table 8. Wheat area, production and yield in the VA and NC study area, according to Quickstats and geospatial data and methods

Virginia	**Produced**				**Predicted**				**Yield Ratio**
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	15014	45901	3.06	56.82	191	877	4.59	85.34	0.67
2009	16471	52286	3.17	59.00	8933	44270	4.96	92.11	0.64
2010	16997	48428	2.85	52.96	1038	4917	4.74	88.05	0.60
2011	18656	82576	4.43	82.27	13464	66595	4.95	91.93	0.89
2012	14245	45169	3.17	58.94	7468	37157	4.98	92.47	0.64
5 year average			*3.34*	*62.00*			*4.84*	*89.98*	*0.69*
North Carolina	**Produced**				**Predicted**				
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	
2008	1012	2591	2.56	47.60	6	20	3.19	59.20	
2009	NoData	NoData	NoData	NoData	54	184	3.42	63.52	
2010	NoData	NoData	NoData	NoData	46	162	3.51	65.20	
2011	NoData	NoData	NoData	NoData	296	1075	3.63	67.47	
2012	NoData	NoData	NoData	NoData	386	1397	3.62	67.36	
5 year average			*2.56*	*47.60*			*3.47*	*64.55*	

Table 9. Barley area, production and yield in the VA and NC study area, according to Quickstats and geospatial data and methods

Virginia	**Produced**				**Predicted**			
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac
2008	3885	3071	0.79	22.04	85	241	2.84	79.30
2009	NoData	NoData	NoData	NoData	381	1066	2.80	78.04
2010	NoData	NoData	NoData	NoData	468	1297	2.77	77.25
2011	NoData	NoData	NoData	NoData	442	1245	2.81	78.46
2012	NoData	NoData	NoData	NoData	468	1294	2.76	77.02
5 year average			*0.79*	*22.04*			*2.80*	*78.01*
North Carolina	**Produced**				**Predicted**			
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac
2008	14771	23845	1.61	45.01	817	2522	3.09	86.04
2009	NoData	NoData	NoData	NoData	468	1381	2.95	82.26
2010	NoData	NoData	NoData	NoData	931	2992	3.22	89.64
2011	NoData	NoData	NoData	NoData	1055	3374	3.20	89.13
2012	NoData	NoData	NoData	NoData	1222	3963	3.24	90.43
5 year average			*1.61*	*45.01*			*3.14*	*87.50*

Table 10. Oats area, production and yield in the VA and NC study area, according to Quickstats and geospatial data and methods

Virginia	**Produced**				**Predicted**			
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac
2008	NoData	NoData	NoData	NoData	223	1288	5.78	92.13
2009	NoData	NoData	NoData	NoData	215	1279	5.95	94.74
2010	NoData	NoData	NoData	NoData	81	464	5.70	90.76
2011	NoData	NoData	NoData	NoData	510	3075	6.03	96.02
2012	NoData	NoData	NoData	NoData	473	2837	6.00	95.56
5 year average			NoData	NoData			5.89	93.84
North Carolina	**Produced**				**Predicted**			
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac
2008	4330	14166	3.27	52.12	221	1206	5.45	86.88
2009	NoData	NoData	NoData	NoData	1871	10950	5.85	93.25
2010	NoData	NoData	NoData	NoData	1321	7225	5.47	87.12
2011	NoData	NoData	NoData	NoData	968	5355	5.53	88.14
2012	NoData	NoData	NoData	NoData	21312	115597	5.42	86.41
5 year average			*3.27*	*52.12*			*5.55*	*88.36*

Table 11. Sorghum area, production and yield in the VA and NC study area, according to Quickstats and geospatial data and methods

North Carolina	**Produced**				**Predicted**			
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac
2008	NoData	NoData	NoData	NoData	819	1965	2.40	38.21
2009	NoData	NoData	NoData	NoData	982	2582	2.63	41.89
2010	NoData	NoData	NoData	NoData	689	1886	2.74	43.59

2011	NoData	NoData	NoData	NoData	463	1342	2.90	46.22
2012	NoData	NoData	NoData	NoData	1065	3184	2.99	47.63
5 year average			NoData	NoData			2.73	43.51

Table 12. Rye area, production and yield in the NC study area, according to Quickstats and geospatial data and methods

North Carolina		**Produced**			**Predicted**				**Yield Ratio**
Year	Area (ha)	Prod. (t)	Yield T/ha	Y lbs/ac	Area (ha)	Prod. (t)	Yield T/ha	Y lbs/ac	
2008	39659	162794	4.10	3662.24	18577	68368	3.68	3283.39	1.12
2009	27114	110767	4.09	3644.78	19942	73306	3.68	3279.55	1.11
2010	35208	105324	2.99	2668.97	25486	93553	3.67	3274.98	0.81
2011	26831	108563	4.05	3609.95	29359	108801	3.71	3306.34	1.09
2012	34843	159755	4.58	4090.59	27487	103190	3.75	3349.33	1.22
5 year average			*3.96*	*3535.31*			*3.70*	*3298.72*	*1.07*

Table 13. Peanuts area, production and yield in the NC study area, according to Quickstats and geospatial data and methods

North Carolina	**Produced**				**Predicted**			
Year	Area (ha)	Prod. (t)	Yield T/ha	Y lbs/ac	Area (ha)	Prod. (t)	Yield T/ha	Y lbs/ac
2008	NoData	NoData	NoData	NoData	172320	154236	0.90	798.55
2009	NoData	NoData	NoData	NoData	173145	154753	0.89	797.41
2010	NoData	NoData	NoData	NoData	263224	235391	0.89	797.84
2011	NoData	NoData	NoData	NoData	369909	329850	0.89	795.56
2012	232087	261400	1.13	1004.86	274451	244439	0.89	794.62
5 year average			1.13	1004.86			0.89	796.80

Table 14. Cotton area, production and yield in the NC study area, according to Quickstats and geospatial data and methods

North Carolina	**Produced**				**Predicted**			
Year	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac	Area (ha)	Prod. (t)	Yield T/ha	Y Bu/ac
2010	NoData	NoData	NoData	NoData	41	189	4.62	73.63
2011	NoData	NoData	NoData	NoData	31	126	4.11	65.53
2012	NoData	NoData	NoData	NoData	50	241	4.81	76.69
3 year average			NoData	NoData			4.52	71.95

Table 15. Triticale area, production and yield in the NC study area, according to Quickstats and geospatial data and methods

State	**Virginia**	**North Carolina**
2012 Database crops area (ha)	816,921	1,523,446
New Area Added (ha)	1,275,471	380,268
Predicted Production (t)	6,184,507	1,519,047
Predicted Average yield (t/ha)	4.85	3.99
Predicted Average yield (bu/ac)	72.1	59.4

Table 16. Summary area, average yield, and total production capacity of new wheat land in Virginia and North Carolina

County	Area suitable (ha)	% county total area
Accomack	4730	3.13%
Amelia	44985	48.51%
Appomattox	22096	25.39%
Brunswick	67006	45.42%
Buckingham	63459	41.98%
Campbell	54182	41.34%
Caroline	21435	15.34%
Charles city	5233	9.87%
Charlotte	62710	50.70%
Chesapeake	589	0.65%
Chesterfield	15008	13.20%
Cumberland	19207	24.67%
Danville	1336	11.74%
Dinwiddie	82510	62.80%
Essex	14120	19.05%
Gloucester	11412	16.71%
Greensville	14997	19.50%
Halifax	76459	35.58%
Hanover	29832	24.32%
Henrico	9756	15.48%
Isle of Wight	16499	17.57%
James city	3548	7.63%
King & Queen	23399	27.67%
King George	9998	20.62%
King William	17425	23.56%
Lancaster	8769	18.34%
Lunenburg	68981	61.59%
Mathews	2139	7.68%
Mecklenburg	82571	46.94%
Middlesex	9236	19.46%
New Kent	3720	6.43%
Northampton	4895	5.33%
Northumberland	8904	15.86%
Nottoway	28775	35.12%
Pittsylvania	132871	52.45%
Prince Edward	27886	30.43%
Prince George	24008	32.93%
Richmond	11285	20.14%
Southampton	49468	31.69%
Spotsylvania	24397	22.90%
Stafford	12598	17.40%
Suffolk	18446	16.59%
Surry	11339	14.12%
Sussex	39241	30.72%
Virginia Beach	447	0.56%

Westmoreland	12466	19.02%
York	963	2.80%

Table 17. Area suitable for conversion in each county/independent city of Virginia

County	Area suitable (ha)	% county total area
Anson	1,141	0.82%
Beaufort	3,722	1.50%
Bertie	10,463	5.45%
Bladen	17,816	7.75%
Brunswick	19,479	7.16%
Camden	126	0.16%
Carteret	3,403	0.98%
Chowan	865	1.43%
Columbus	21,391	8.66%
Craven	4,971	2.48%
Cumberland	7,909	4.64%
Currituck	338	0.25%
Dare	123	0.03%
Duplin	30,068	14.13%
Edgecombe	14,083	10.73%
Gates	3,758	4.20%
Greene	4,776	6.92%
Halifax	13,452	7.10%
Harnett	15,433	9.91%
Hertford	3,325	3.56%
Hoke	3,155	3.11%
Hyde	9	0.00%
Johnston	17,816	8.65%
Jones	4,288	3.50%
Lee	1,709	2.55%
Lenoir	5,249	5.03%
Martin	4,033	3.37%
Montgomery	16,262	12.51%
Moore	7,557	4.13%
Nash	25,220	17.94%
New Hanover	431	0.51%
Northampton	9,561	6.70%
Onslow	15,574	6.64%
Pamlico	3,149	2.15%
Pasquotank	147	0.20%
Pender	21,845	9.04%
Perquimans	572	0.67%
Pitt	6,310	3.72%
Richmond	2,947	2.37%
Robeson	16,504	6.70%
Sampson	16,944	6.91%

Scotland	2,886	3.48%
Stanly	973	0.93%
Tyrrell	198	0.13%
Union	4,469	2.70%
Washington	852	0.78%
Wayne	6,551	4.54%
Wilson	8,425	8.70%

Table 18. Area suitable for conversion in each county city of North Carolina

	Ferguson (m^3 * 1000)			Zhang-Budyko (m^3 * 1000)		
	CDL 2012	After	%diff	CDL 2012	After	%diff
Virginia	33,182	38,413	15.76	29,025	63,476	118.69
Accomack	1,182	1,191	0.71	1,572	1,679	6.81
Amelia	484	668	37.94	372	1,629	337.78
Appomattox	548	636	16.20	416	1,032	148.11
Brunswick	859	1,145	33.30	452	2,450	441.50
Buckingham	824	1,077	30.75	538	2,351	337.28
Campbell	851	1,062	24.83	637	2,082	226.89
Caroline	812	904	11.39	616	1,150	86.64
Charles city	510	534	4.71	356	498	39.69
Charlotte	717	966	34.78	542	2,254	315.89
Chesapeake	1,544	1,546	0.12	1,081	1,094	1.24
Chesterfield	920	985	6.99	642	1,069	66.35
Cumberland	403	479	18.94	276	823	197.95
Danville	65	71	8.15	98	134	36.70
Dinwiddie	898	1,259	40.13	592	2,952	398.54
Essex	499	558	11.88	483	819	69.72
Gloucester	612	664	8.50	343	658	91.67
Greensville	930	995	6.98	397	802	102.05
Halifax	1,133	1,438	26.88	986	3,049	209.34
Hanover	1,104	1,222	10.72	633	1,370	116.40
Henrico	563	609	8.16	626	869	38.73
Isle of Wight	1,042	1,112	6.67	726	1,197	64.97
James city	326	343	5.18	358	460	28.49
King & Queen	642	758	18.09	407	1,003	146.52
King George	294	332	12.64	453	659	45.43
King William	582	658	13.11	471	895	90.02
Lancaster	174	212	21.95	837	1,071	27.98
Lunenburg	572	852	48.93	342	2,229	551.92
Mathews	327	336	2.64	215	261	21.52
Mecklenburg	1,004	1,323	31.77	1,352	3,475	157.11
Middlesex	279	316	13.20	248	482	94.66
New Kent	376	390	3.77	365	462	26.49
Northampton	358	363	1.46	199	273	37.16
Northumberland	286	321	12.13	1,357	1,588	16.99
Nottoway	489	601	22.98	693	1,532	120.92

Pittsylvania	1,168	1,654	41.54	1,190	4,773	301.05
Prince Edward	596	706	18.50	683	1,441	110.92
Prince George	779	886	13.79	513	1,153	124.77
Richmond	359	407	13.36	329	616	86.99
Southampton	1,664	1,897	14.01	1,145	2,508	118.99
Spotsylvania	795	902	13.55	683	1,322	93.45
Stafford	502	555	10.64	627	925	47.52
Suffolk	1,411	1,494	5.94	1,267	1,790	41.24
Surry	686	737	7.36	535	836	56.40
Sussex	1,326	1,510	13.85	788	1,858	135.94
Virginia Beach	857	857	0.00	531	541	1.81
Westmoreland	460	509	10.50	376	658	75.05
Williamsburg	19	19	0.59	22	22	-0.07
York	349	352	0.92	653	680	4.24

Table 19. Runoff in Virginia, before and after conversion for both runoff methods by county

	Ferguson (m^3 * 1000)			Zhang-Budyko (m^3 * 1000)		
	CDL 2012	After	%diff	CDL 2012	After	%diff
North Carolina	87,934	88,286	0.40	81,097	90,061	11.05
Anson	1,281	1,284	0.20	345	374	8.46
Beaufort	3,881	3,806	-1.92	2,789	2,880	3.27
Bertie	3,042	3,032	-0.34	1,455	1,721	18.22
Bladen	3,134	3,156	0.69	1,930	2,294	18.89
Brunswick	3,459	3,475	0.47	4,753	5,301	11.53
Camden	1,222	1,218	-0.33	565	566	0.20
Carteret	2,531	2,527	-0.15	3,268	3,349	2.50
Chowan	670	661	-1.25	539	557	3.32
Columbus	3,929	3,918	-0.28	2,485	2,977	19.84
Craven	3,324	3,312	-0.36	3,008	3,131	4.09
Cumberland	1,590	1,610	1.28	1,261	1,417	12.45
Currituck	1,067	1,066	-0.12	990	996	0.62
Dare	1,783	1,787	0.20	1,162	1,159	-0.19
Duplin	2,394	2,501	4.46	14,137	14,378	1.70
Edgecombe	1,376	1,408	2.32	903	1,216	34.72
Gates	1,482	1,479	-0.25	781	890	13.88
Greene	760	765	0.62	719	838	16.65
Halifax	2,050	2,084	1.69	840	1,200	42.95
Harnett	1,212	1,246	2.77	860	1,270	47.80
Hertford	1,396	1,389	-0.54	751	841	11.98
Hoke	754	755	0.02	606	677	11.69
Hyde	3,178	3,175	-0.10	3,180	3,175	-0.16
Johnston	2,003	2,045	2.06	1,376	1,860	35.12
Jones	2,293	2,259	-1.49	1,718	1,831	6.58
Lee	486	487	0.16	246	301	22.23
Lenoir	1,240	1,240	0.07	1,157	1,282	10.83
Martin	1,889	1,865	-1.26	966	1,058	9.45

Montgomery	622	682	9.72	394	870	120.72
Moore	1,176	1,210	2.90	704	941	33.64
Nash	1,141	1,199	5.10	617	1,319	113.70
New Hanover	678	679	0.11	1,761	1,774	0.73
Northampton	1,822	1,838	0.86	1,147	1,384	20.67
Onslow	2,853	2,845	-0.28	4,115	4,543	10.39
Pamlico	1,709	1,700	-0.49	1,888	1,968	4.23
Pasquotank	1,085	1,086	0.10	755	757	0.28
Pender	3,829	3,843	0.36	3,587	4,150	15.71
Perquimans	1,150	1,132	-1.57	806	818	1.54
Pitt	2,543	2,543	0.01	1,733	1,883	8.65
Richmond	646	656	1.53	451	529	17.18
Robeson	3,098	3,101	0.09	1,434	1,754	22.31
Sampson	2,361	2,413	2.21	2,457	2,790	13.53
Scotland	720	717	-0.42	236	300	27.44
Stanly	1,005	1,003	-0.16	470	497	5.64
Tyrrell	2,141	2,137	-0.17	1,392	1,399	0.52
Union	1,613	1,627	0.86	522	633	21.23
Washington	1,756	1,740	-0.89	1,737	1,758	1.18
Wayne	1,478	1,493	1.03	1,379	1,523	10.44
Wilson	1,083	1,094	1.03	723	931	28.74

Table 20. Runoff in North Carolina, before and after conversion for both runoff methods by county

	Before		After		Ratio total erosion A/B
	Total (Gg)	Average (t/ha)	Total (Gg)	Average (t/ha)	
Virginia	5018	1.19	55258	13.05	11.01
Accomack	58	0.57	70	0.69	1.20
Amelia	155	1.64	1573	16.70	10.18
Appomattox	62	0.70	1036	11.64	16.60
Brunswick	115	0.76	3205	21.27	27.81
Buckingham	97	0.63	3587	23.30	37.06
Campbell	138	1.04	3659	27.40	26.48
Caroline	218	1.55	618	4.41	2.84
Charles city	78	1.62	155	3.23	1.99
Charlotte	135	1.07	3369	26.79	24.96
Chesapeake	19	0.23	21	0.26	1.11
Chesterfield	44	0.40	578	5.16	13.03
Cumberland	37	0.47	675	8.55	18.13
Danville	3	0.26	72	6.27	24.24
Dinwiddie	165	1.24	3336	25.08	20.16
Essex	162	2.38	438	6.45	2.71
Gloucester	44	0.79	187	3.35	4.27
Greensville	123	1.59	492	6.35	3.99
Halifax	128	0.59	3120	14.39	24.31
Hanover	192	1.54	1032	8.29	5.38
Henrico	57	0.92	253	4.09	4.43

Isle of Wight	141	1.72	356	4.36	2.53
James city	22	0.60	117	3.17	5.32
King & Queen	132	1.60	504	6.10	3.81
King George	64	1.37	301	6.42	4.71
King William	88	1.24	360	5.03	4.08
Lancaster	42	1.24	153	4.46	3.60
Lunenburg	131	1.15	3965	34.58	30.20
Mathews	5	0.24	16	0.76	3.14
Mecklenburg	344	2.07	4971	29.96	14.47
Middlesex	52	1.53	200	5.92	3.88
New Kent	65	1.17	125	2.27	1.94
Northampton	32	0.80	45	1.10	1.39
Northumberland	112	2.26	244	4.91	2.18
Nottoway	85	1.02	1231	14.75	14.52
Pittsylvania	301	1.17	7822	30.37	25.97
Prince Edward	55	0.59	1487	16.02	26.94
Prince George	81	1.17	578	8.34	7.14
Richmond	103	2.05	359	7.11	3.47
Southampton	354	2.27	1196	7.66	3.38
Spotsylvania	129	1.21	1251	11.78	9.73
Stafford	88	1.23	694	9.73	7.92
Suffolk	99	0.97	250	2.44	2.53
Surry	106	1.46	259	3.57	2.44
Sussex	162	1.26	737	5.74	4.54
Virginia Beach	18	0.29	19	0.31	1.07
Westmoreland	172	2.86	510	8.49	2.97
Williamsburg	0	0.12	0	0.15	1.24
York	3	0.12	31	1.13	9.42

Table 21. Erosion before and after conversion in Virginia calculated by RUSLE 3d with a maximum flow accumulation limit

	Before		After		Ratio total erosion A/B
	Total (Gg)	Average (t/ha)	Total (Gg)	Average (t/ha)	
North Carolina	6048	1.03	10716	1.82	1.77
Anson	206	1.63	233	1.84	1.13
Beaufort	120	0.63	138	0.73	1.15
Bertie	180	1.12	257	1.60	1.42
Bladen	85	0.42	174	0.85	2.04
Brunswick	47	0.24	151	0.78	3.24
Camden	19	0.35	20	0.36	1.03
Carteret	27	0.25	46	0.42	1.71
Chowan	46	1.14	56	1.41	1.23
Columbus	169	0.78	267	1.23	1.58
Craven	103	0.63	143	0.87	1.38
Cumberland	66	0.43	105	0.69	1.59
Currituck	24	0.42	24	0.42	1.00

Dare	6	0.07	6	0.07	0.99
Duplin	244	1.28	361	1.90	1.48
Edgecombe	194	1.65	289	2.45	1.49
Gates	60	0.76	84	1.07	1.42
Greene	136	2.19	176	2.82	1.29
Halifax	237	1.39	434	2.55	1.83
Harnett	219	1.56	544	3.87	2.48
Hertford	120	1.46	162	1.97	1.35
Hoke	87	0.95	98	1.07	1.13
Hyde	10	0.08	10	0.08	0.98
Johnston	343	1.85	606	3.26	1.77
Jones	87	0.79	110	1.01	1.27
Lee	75	1.23	137	2.25	1.83
Lenoir	102	1.09	132	1.41	1.29
Martin	148	1.39	181	1.70	1.22
Montgomery	79	0.67	1064	9.06	13.55
Moore	96	0.58	298	1.80	3.11
Nash	215	1.70	974	7.67	4.52
New Hanover	6	0.15	9	0.26	1.68
Northampton	199	1.58	285	2.26	1.43
Onslow	95	0.54	213	1.21	2.23
Pamlico	18	0.24	48	0.63	2.65
Pasquotank	30	0.58	30	0.59	1.02
Pender	65	0.34	217	1.11	3.31
Perquimans	43	0.75	48	0.84	1.12
Pitt	177	1.17	209	1.38	1.18
Richmond	44	0.39	174	1.55	3.99
Robeson	134	0.61	177	0.80	1.32
Sampson	216	0.98	306	1.39	1.42
Scotland	22	0.30	34	0.46	1.54
Stanly	427	4.51	467	4.93	1.09
Tyrrell	15	0.17	15	0.18	1.02
Union	609	3.99	703	4.61	1.15
Washington	34	0.43	38	0.48	1.12
Wayne	168	1.30	215	1.66	1.28
Wilson	196	2.27	249	2.88	1.27

Table 22. Erosion before and after conversion in North Carolina calculated by RUSLE 3d with a maximum flow accumulation limit

	Before		After		Ratio total erosion A/B
	Total (Gg)	Average (t/ha)	Total (Gg)	Average (t/ha)	
Virginia	3028	0.80	15515	4.10	5.12
Accomack	35	0.39	19	0.21	0.54
Amelia	96	1.13	456	5.37	4.77
Appomattox	37	0.46	281	3.49	7.66
Brunswick	70	0.51	925	6.79	13.29

Buckingham	54	0.39	1016	7.28	18.68
Campbell	84	0.69	1023	8.46	12.25
Caroline	135	1.07	173	1.37	1.29
Charles city	49	1.14	41	0.97	0.85
Charlotte	80	0.71	959	8.47	12.01
Chesapeake	12	0.18	6	0.08	0.47
Chesterfield	26	0.26	163	1.62	6.24
Cumberland	22	0.31	185	2.59	8.38
Danville	2	0.16	19	1.87	11.66
Dinwiddie	102	0.85	982	8.20	9.64
Essex	99	1.62	118	1.94	1.19
Gloucester	26	0.51	46	0.92	1.80
Greensville	76	1.12	132	1.93	1.73
Halifax	74	0.38	880	4.50	11.86
Hanover	118	1.05	292	2.60	2.47
Henrico	34	0.63	68	1.24	1.98
Isle of Wight	84	1.16	91	1.25	1.08
James city	13	0.40	28	0.87	2.19
King & Queen	78	1.05	131	1.77	1.69
King George	38	0.90	81	1.93	2.13
King William	51	0.80	92	1.44	1.79
Lancaster	25	0.82	38	1.23	1.50
Lunenburg	77	0.74	1139	10.96	14.88
Mathews	3	0.16	4	0.21	1.36
Mecklenburg	207	1.38	1426	9.52	6.89
Middlesex	31	1.00	50	1.65	1.64
New Kent	39	0.80	32	0.65	0.82
Northampton	19	0.55	12	0.34	0.62
Northumberland	66	1.47	61	1.38	0.93
Nottoway	50	0.66	344	4.55	6.86
Pittsylvania	180	0.77	2181	9.36	12.15
Prince Edward	32	0.38	418	4.98	13.00
Prince George	49	0.80	154	2.50	3.13
Richmond	63	1.38	96	2.10	1.52
Southampton	224	1.64	327	2.39	1.46
Spotsylvania	79	0.82	350	3.65	4.45
Stafford	51	0.79	196	3.05	3.84
Suffolk	60	0.66	63	0.70	1.05
Surry	64	0.98	65	1.00	1.03
Sussex	101	0.88	199	1.75	1.98
Virginia Beach	11	0.21	5	0.10	0.47
Westmoreland	104	1.93	138	2.56	1.32
Williamsburg	0	0.08	0	0.04	0.53
York	2	0.08	8	0.32	4.16

Table 23. Erosion before and after conversion in Virginia calculated by RUSLE 3d with a maximum flow accumulation limit and USPED eroded areas mask

	Before		After		Ratio total
	Total (Gg)	Average (t/ha)	Total (Gg)	Average (t/ha)	erosion A/B
North Carolina	4028	0.72	3068	0.55	0.76
Anson	139	1.10	69	0.55	0.50
Beaufort	78	0.44	37	0.21	0.48
Bertie	120	0.78	72	0.47	0.60
Bladen	56	0.30	48	0.25	0.86
Brunswick	30	0.16	39	0.21	1.30
Camden	12	0.24	5	0.10	0.43
Carteret	18	0.18	12	0.11	0.64
Chowan	30	0.79	15	0.40	0.51
Columbus	112	0.54	73	0.36	0.65
Craven	69	0.45	38	0.25	0.56
Cumberland	42	0.29	29	0.20	0.69
Currituck	15	0.30	6	0.13	0.43
Dare	4	0.06	2	0.02	0.41
Duplin	161	0.87	98	0.53	0.61
Edgecombe	130	1.15	83	0.74	0.64
Gates	40	0.53	24	0.31	0.59
Greene	91	1.50	50	0.81	0.54
Halifax	157	0.95	128	0.77	0.81
Harnett	144	1.04	158	1.14	1.10
Hertford	80	0.99	46	0.57	0.57
Hoke	56	0.64	27	0.31	0.49
Hyde	6	0.06	3	0.03	0.40
Johnston	225	1.24	173	0.95	0.77
Jones	59	0.57	30	0.29	0.51
Lee	48	0.80	39	0.65	0.81
Lenoir	69	0.76	37	0.41	0.54
Martin	98	0.97	51	0.50	0.51
Montgomery	51	0.43	314	2.68	6.16
Moore	61	0.37	84	0.51	1.38
Nash	143	1.14	295	2.36	2.07
New Hanover	4	0.11	2	0.07	0.65
Northampton	132	1.08	81	0.66	0.61
Onslow	63	0.37	56	0.33	0.88
Pamlico	11	0.16	12	0.17	1.06
Pasquotank	19	0.40	8	0.17	0.43
Pender	43	0.23	57	0.31	1.34
Perquimans	28	0.52	13	0.24	0.47
Pitt	118	0.81	58	0.40	0.49
Richmond	28	0.25	50	0.45	1.81
Robeson	89	0.45	50	0.25	0.56
Sampson	142	0.68	85	0.41	0.60
Scotland	15	0.21	10	0.14	0.67
Stanly	297	3.15	141	1.49	0.48

Tyrrell	9	0.14	4	0.06	0.42
Union	422	2.78	213	1.41	0.51
Washington	22	0.32	10	0.15	0.46
Wayne	112	0.89	60	0.48	0.54
Wilson	131	1.56	71	0.85	0.54

Table 24. Erosion before and after conversion in North Carolina calculated by RUSLE 3d with a maximum flow accumulation limit and USPED eroded areas mask

	Before		After		Ratio total erosion A/B
	Total (Gg)	Average (t/ha)	Total (Gg)	Average (t/ha)	
Virginia	220	0.06	2279	0.60	10.37
Accomack	3	0.04	4	0.05	1.23
Amelia	6	0.07	59	0.69	9.50
Appomattox	3	0.04	52	0.64	16.78
Brunswick	5	0.04	120	0.88	24.70
Buckingham	5	0.04	155	1.11	30.15
Campbell	6	0.05	154	1.27	25.76
Caroline	9	0.07	26	0.21	2.81
Charles city	3	0.07	6	0.14	1.99
Charlotte	6	0.06	137	1.21	21.95
Chesapeake	1	0.01	1	0.01	1.14
Chesterfield	2	0.02	24	0.23	11.15
Cumberland	2	0.02	29	0.41	16.79
Danville	0	0.02	4	0.35	22.81
Dinwiddie	7	0.05	114	0.95	17.34
Essex	7	0.11	19	0.30	2.79
Gloucester	2	0.04	10	0.20	4.91
Greensville	4	0.07	18	0.26	4.01
Halifax	6	0.03	134	0.68	20.78
Hanover	8	0.07	40	0.36	5.26
Henrico	2	0.04	10	0.19	4.29
Isle of Wight	7	0.09	19	0.26	2.85
James city	1	0.04	8	0.26	7.14
King & Queen	6	0.08	26	0.34	4.14
King George	3	0.07	14	0.34	5.00
King William	5	0.07	19	0.30	4.20
Lancaster	2	0.07	8	0.27	3.96
Lunenburg	6	0.06	164	1.58	25.65
Mathews	0	0.02	1	0.06	3.26
Mecklenburg	15	0.10	193	1.29	12.69
Middlesex	3	0.09	11	0.36	4.07
New Kent	3	0.06	6	0.12	2.02
Northampton	2	0.06	3	0.08	1.40
Northumberland	6	0.13	13	0.30	2.36
Nottoway	4	0.06	53	0.70	12.53
Pittsylvania	13	0.06	320	1.37	24.81

Prince Edward	3	0.03	62	0.74	22.29
Prince George	3	0.05	23	0.38	7.35
Richmond	4	0.10	18	0.40	4.15
Southampton	12	0.09	42	0.31	3.41
Spotsylvania	5	0.06	49	0.51	8.91
Stafford	4	0.07	31	0.48	7.10
Suffolk	5	0.05	13	0.15	2.94
Surry	5	0.07	13	0.19	2.75
Sussex	6	0.05	26	0.23	4.55
Virginia Beach	1	0.02	1	0.02	1.08
Westmoreland	7	0.13	25	0.47	3.49
Williamsburg	0	0.01	0	0.01	1.17
York	0	0.01	2	0.09	9.94

Table 25. Erosion before and after conversion in Virginia calculated by USPED with a maximum flow accumulation limit

	Before		After		Ratio total erosion A/B
	Total (Gg)	Average (t/ha)	Total (Gg)	Average (t/ha)	
North Carolina	321	0.06	564	0.10	1.76
Anson	11	0.09	12	0.09	1.11
Beaufort	8	0.05	10	0.06	1.15
Bertie	10	0.06	14	0.09	1.45
Bladen	5	0.02	10	0.05	2.15
Brunswick	3	0.02	10	0.05	3.17
Camden	1	0.03	1	0.03	1.03
Carteret	2	0.02	3	0.03	1.65
Chowan	3	0.08	4	0.10	1.26
Columbus	9	0.04	15	0.07	1.65
Craven	7	0.04	9	0.06	1.42
Cumberland	4	0.03	6	0.05	1.69
Currituck	2	0.03	2	0.03	0.99
Dare	0	0.01	0	0.01	0.99
Duplin	13	0.07	20	0.11	1.55
Edgecombe	10	0.09	15	0.13	1.55
Gates	3	0.05	5	0.06	1.37
Greene	6	0.10	8	0.14	1.32
Halifax	11	0.07	22	0.13	1.89
Harnett	11	0.08	26	0.19	2.44
Hertford	6	0.08	9	0.11	1.35
Hoke	5	0.05	5	0.06	1.13
Hyde	1	0.01	1	0.01	0.98
Johnston	17	0.09	30	0.16	1.78
Jones	5	0.05	7	0.06	1.30
Lee	4	0.07	7	0.11	1.73
Lenoir	5	0.06	7	0.08	1.32
Martin	8	0.08	10	0.10	1.24

Montgomery	5	0.04	52	0.44	11.42
Moore	5	0.03	15	0.09	2.86
Nash	10	0.08	46	0.37	4.53
New Hanover	0	0.01	1	0.02	1.62
Northampton	9	0.08	14	0.11	1.47
Onslow	6	0.03	13	0.08	2.25
Pamlico	1	0.02	4	0.05	2.61
Pasquotank	2	0.05	2	0.05	1.02
Pender	4	0.02	14	0.08	3.28
Perquimans	3	0.06	4	0.07	1.13
Pitt	10	0.07	12	0.08	1.20
Richmond	2	0.02	9	0.08	3.71
Robeson	7	0.04	10	0.05	1.35
Sampson	11	0.05	16	0.08	1.48
Scotland	1	0.02	2	0.03	1.58
Stanly	20	0.22	22	0.24	1.09
Tyrrell	1	0.02	1	0.02	1.01
Union	31	0.20	35	0.23	1.13
Washington	2	0.03	3	0.04	1.12
Wayne	9	0.07	11	0.09	1.32
Wilson	9	0.11	12	0.15	1.31

Table 26. Erosion before and after conversion in North Carolina calculated by USPED with a maximum flow accumulation limit

Conclusions

The convergence of ever increasing amounts of georeferenced information, improved computing power, the availability of geospatial software and of properly trained personnel has led to a number of novel geospatial applications. Remote Sensing has increased quantification in Geography, Environmental studies and other disciplines where spatial location is a parameter causing fundamental change. It facilitates the emergence of quantitative laws to explain the landscape, potentially leading to the emergence of an improved quantitative framework for these disciplines. This dissertation sought to increase the quality of our knowledge of ecosystem services through improved quantitative information. I sought to help advance the discussion on ecosystem services provided by agriculture from a qualitative descriptive discourse into a quantitative inventory. Geospatial tools provided the means to produce such estimates and showcase some of the broader benefits of agriculture. For chapters one and two I limited the study area to four counties in eastern Virginia, so as to become more familiar with the datasets used and their limitations. For the last chapter I expanded the study area to cover the main agricultural regions of Virginia and North Carolina.

My first task was to evaluate the quality of the available geospatial layers. I selected the highest resolution datasets available, NLCD and CDL and validated in a simplified agriculture/not agriculture scheme them using high resolution NAIP imagery. Before my work there had been any independent validation of these land cover layers in the four county area. I am proud of the work I have done and can expect that my work will be cited by those engaged in this task in the future. I found that there is room for improvement of the agricultural land cover layers. The fact that these layers are made using state of the art methods, having access to considerable ancillary data and still fall short of where I would prefer them to be, is an indicator that there is room for advancement in the process of classification. The outcome of my validation was consistent with that of other validation studies for NLCD and CDL: accuracy of each land cover class increases as its proportion in the layer and the landscape increases and while there are significant errors of omission and commission, they tend to cancel out and give a relative proportion number for each class close to the ground truth. Furthermore it is difficult for most layers including the reference layer used, to consistently distinguish between row crops and pastures or pastures and other grasses (such as golf courses). NLCD consistently displayed comparatively high quality across the years. This could be due to the fact that I used the 1992-2001 retrofit change detection layer, for which NLCD 1992 was redone using the 2001 methodology. I wish to suggest to the Multi Resolution Land Consortium to remake NLCD a few years after it is released, just as the European Environmental Agency regularly updates CORINE Land Cover using newer information[4]. The first Cropland Data Layer of our study area, CDL 2002, suffers from quality issues that excluded it from most later uses in this dissertation. It was used after several treatments to increase accuracy for the calculation of ecosystem services in the second chapter but not used to extract agricultural productivity for the third chapter. Over time though the accuracy of CDL has increased and its creators have added more classes, which better capture the variety and extent of agriculture. This improvement is a general trend; there are several outliers which tend to be concentrated to years where there were strong climatic variations such as drought.

[4] CORINE Land Cover 2000 is currently on version 16, released on April 2012

The extent of the broad category of "agricultural land" proved relatively stable across the 19 years studied in the four counties. There were annual variations in the extent of all agricultural land which were within a short 2% range for the 19 years studied. This was corroborated by data from manuscript three, which showed no overarching long term trend in the extent of specific crops for 2008-2012 in the broader region of eastern Virginia and North Carolina. It seems that farmers did change the specific area and location of crops planted in particular year over the same fields. I did not see large areas of formerly non agricultural land entering agriculture or agricultural land being lost to urbanization. Since the extent of agricultural land did not show considerable change and each land cover layer was generally showing the same fields, use of multitemporal data in the form of validated labels in cadastral parcels was more accurate at showing the extent of agriculture one particular year than the dataset of that specific year. The use of cadastral parcels gave a framework that greatly facilitated validation through photointerpretation. Whether it can give a framework to improve the quality of the agricultural land cover layer is open for further research. Its use for delineation changes slightly the extent and distribution of agricultural land at each layer. The use of parcels reduced the proportion of agriculture in each of the four counties. There was no obvious specific algorithmic combination of the land cover labels of the pixels that could give an improved output of the specific location and distribution of agriculture for all four counties, though again this is open to further research.

Geospatial data revealed that among the four counties studied more intensively there was a reduction in the extent of agriculture for three of them and an increase at Charles City County. All of them saw an increase in population that was associated with the construction of more dwellings. However these dwellings were mostly constructed in non agricultural land such as forests, which throughout the period and today is the majority land cover in all 4 counties. It seems that agricultural land is extensively lost only after a tipping point is reached where other land covers are less available. Chesterfield county seems to have passed that tipping point during the 19 years studied and Henrico seemed on its verge, but the fast growing in population Albemarle county only saw gradual change in the area covered by agricultural land. Extracting these trends in the extent of agriculture required more effort than simple comparison among the raw land cover layers. They were subtle enough that the trend was lost among the noise of the interannual discrepancies among the layers. It was only after validation created a high accuracy dataset that they became apparent. Validation also had another advantage: it created a more accurate land cover layer which could be used to quantify ecosystem services provided by agriculture.

This dataset was used as an input in geospatial models to quantify various ecosystem services. A variety of such models exists. InVEST is a collection of models that quantify a subset of ecosystem services at multiple scales. I eventually used its water yield model in the third manuscript. For the second manuscript though I found in the literature several other models that had used statistical information from the Census and the Survey of Agriculture to calculate some services. I decided to adapt them to the geospatial domain, use as input crop extent from validated CDL and the production output from VALUES to calculate said ecosystem services. I selected for study services directly tied to crop production and living biomass which were easier to calculate. Net Primary Productivity for agriculture was proximate to values given in the literature for forest ecosystems in North Carolina. Unfortunately most model outputs could not be validated from independent information. Validation was possible for production area, volume and yield for the VALUES crops with data collected during the Survey of Agriculture. Although the data was lacunose due to NASS guidelines to preserve farmer confidentiality, it showed that while area under most crops matched both datasets, actual yield was consistently less than soil based yield predicted by VALUES. I should note though that Survey crop area numbers are not independently produced from CDL. NASS, which produces both datasets, has been using pre-production CDL to inform the Survey of Agriculture after 2010. I could not validate most of the other outputs of the ecosystem services models; I leave this task for future researchers. Finally I modelled what financial output of agriculture during the study period, so that the value of the crops can be compared to the value of ecosystem services, if such markets ever arise.

While the four counties gave an in depth look into the variety of agricultural practices in Virginia, I sought in my third manuscript to broaden the spatial extent to a larger study area comprised from eastern Virginia and North Carolina. Using a dataset that was not available at the time I started this dissertation, gridded SSURGO, I rasterized VALUES and its North Carolina equivalent RYE so as to facilitate production and productivity comparisons for a study area that included most agricultural land in Virginia and North Carolina. I used predicted yields from CDL and VALUES or RYE and actual yields from Quickstats. Since CDL has now been available for a sufficient time, I compare predicted estimate yield over a five year period, to see if it was matched by actual yield for three of those years. VALUES and RYE had not previously been subjected to this sort of quantitative validation with field estimates and I am proud of my pioneering work.

At the scale of the study area produced yield rarely matched or exceed predicted yield. Notable exceptions were soybeans (3 out of 5) and peanuts (4 out of 5) for North Carolina. This has several implications: On the one hand adaptation of better farm management practices can lead to an increase by over 280,000 tons of corn and 75,000 tons of wheat in Virginia for 2012 alone. On the other hand if current nutrient applications are based on predicted yield, then farmers are not using their nutrient efficiently, leading to economic and environmental disservices. Yield gaps further present evidence whether updates of the yield databases are on target, or outdated. Produced Yield is higher than Predicted Yield only for 9 out of 40 crop year combinations. If it had met the 3 out of 5 year goal, that should have been 24 out of 40. A more systematic process should be implemented to regularly update the databases to maintain realism. To this day updates have been haphazard; they took place when farmers complained that the predicted yield no longer corresponded to their yield, especially in view of their need to use manure as fertilizer which is legislatively limited through VALUES.

Even partial knowledge of ecosystem services can help inform decisions on the tradeoffs necessary to achieve various goals. Local grain feed production is unable to meet local needs. Through the use of the geospatial tools I was able to model potential production and several ecosystem disservices if there is to be agricultural expansion into land that is currently under different use. I selected and quantified land for conversion based on conservative criteria that considered only the most productive lands and excluded lands unlikely to be converted. In Virginia the extent of selected land was equal of 1,275,471 ha or 1.5 times the 2012 extent of the six crops in the VALUES database. In North Carolina it was equal to 380,268 ha or 25% of the 2012 extent of the ten crops in the RYE database. Random visual inspection of land selected for conversion revealed that potential new land belonged mostly to contiguous blocks rather than isolated pixels spread across the landscape. Future work may address the question of why this land, if so productive, is not in agricultural use and why in Virginia there more suitable land than in North Carolina.

An increase in the quantity of crops produced in the study are would also have positive economic impacts, in that it would increase economic activity in the area and strengthen the community. If we were to convert the selected land into agriculture, in addition to its social and economic impacts, this would entail large scale modifications in hydrology and erosion. I have modelled changes to runoff and erosion using geospatial models that normally are not applied to agricultural land. Runoff models agreed that runoff yield would be increased in both state, more in Virginia than in North Carolina. They disagreed though in the extent of this increase. Erosion will be increased five or 11 times in Virginia and will either be reduced 25% or increased by 76% in North Carolina. This general picture glosses over very significant quantitative and qualitative differences at the county level which further show the need to validate the models with field data. I would suggest that as a next step a smaller area be selected to be modelled at higher resolution and with better data than I have used. Furthermore the results of modelling can only be strengthened if they can be validated with field information, if such validation is possible. This will help reveal discrepancies in the models used and my implementation of them, which can be the cause of several unrealistic outputs I have produced.

The use of geospatial tools using multiple data sets in unique combinations has opened an avenue into investigations that allows better understanding of agriculture and its holistic impact on the ecosystem. I have attempted to quantify a variety of ecosystem services so that we can be informed of the potential tradeoffs of our possible choices. While I have attempted to validate the outputs of my work, it was not possible to do so for all of them. It is now the job of other researchers to question my methods and my results so as to improve them, to validate what I could not do so and to use my conclusions to further investigate both the questions I have raised and those that my research raises to them.