Final Report

Assessing the Feasibility and Development of a Forage Insurance Plan using Satellite-Derived Biophysical Parameters with a Focus on the Provinces of Alberta and Saskatchewan, Canada

March 31, 2018

Project Number: 63302-ARI-IAR-2016 and Project Number: 23059-ARI-IAR-2016

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SECTION 1

Executive Summary

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Forage includes plant material eaten by grazing livestock, or pasture land and also similar plants cut for fodder. The forage industry is heterogeneous and has several distinct sectors based on the end use of the forage crop. Forage includes both annual and perennial crops, which are usually harvested as silage, greenfeed or swath grazing, and grazed as pasture, harvested as greenfeed, stored as hay or silage, processed into pellets (alfalfa, etc.), cubes or compressed hay for domestic and export markets, respectively.

In Canada, forage crops have received coverage under AgriInsurance (crop insurance) since 1967, however, participation rates have been relatively low at approximately 10 to 20% of the potential land area, compared to approximately 70 to 85% for other crops, such as wheat, canola, corn, etc. This has left the sector particularly vulnerable in times of substantial forage shortages due to adverse weather, leaving producers unable to produce or purchase the forage they need to feed their livestock, or to re-establish their forage. As a result of this forage and livestock industry risk, there has been pressure on Federal, Provincial and Territorial governments to provide disaster-related assistance. Since 2008, there have been four AgriRecovery initiatives in response to pasture or forage related issues, with government providing payments to producers totaling $148 million. Therefore, improving forage and pasture insurance, and increasing participation rates among producers has been identified as a priority for federal and provincial governments.

1.1. Forage Insurance Challenges

Traditional insurance programs used for other crops do not always work well for forage. For example, forage management systems may vary greatly from one farm to another, and may also change according to annual weather conditions. In addition, forage may be harvested multiple times throughout the growing season and/or grazed by livestock. When forage is produced directly for feed, it is often not accounted for by the producer because the producer may let their livestock feed on forage fields as necessary and do not calculate how much feed is consumed. Due to these reasons, accurate insurance loss estimates for forage are difficult to achieve even when relying on costly, and time-consuming, human expertise. Collectively, these challenges make it difficult to design a relevant forage insurance program and determine actuarially fair and sustainable premium rates. As a result, index-based insurance is thought to be an alternative framework for developing forage insurance. With index-based insurance, the insurance payout is linked to an index, such as rainfall, temperature, or satellite, rather than the actual loss on the farm. Therefore, an index-based insurance approach may solve some of the problems that limit the application of traditional crop insurance in the case of forages.

1.2. Index Insurance Benefits and Challenges

Index-insurance may provide several advantages over traditional insurance, including lower transaction costs, fast and transparent settlement, and less adverse selection and less moral hazard. Cost efficiencies may be realized in theory since the insurance payouts are determined automatically from the index, rather than on-farm loss adjustments, which can be costly. The index should be constructed from underlying data that is transparent, reliable and representative. Information asymmetry problems, such as adverse selection and moral hazard, can also largely often be avoided given that the individual loss characteristics of the producer often cannot influence the underlying index and the producers ability to collect an insurance payout. Despite the many benefits of index insurance, developing an index that is representative and suitable for the individual producer can be a major challenge. This difficulty is referred to as basis risk, in which the index differs from the actual farm-level yield. This can refer to situations where a producer suffers a loss, yet, the index does not trigger an insurance payout, or alternatively when the index determines an insurance payout, but, the producer does not suffer a loss on the farm.

Weather stations have traditionally been the primary data source for agricultural weather index insurance programs (e.g. temperature, rainfall, etc.). However, in many cases there are spatial data limitations in terms of the density of weather stations, and temporal data limitations due to the frequency of observations (time series) available from each weather station. Most research in this area has examined various interpolation techniques to help address this in order to enable the prediction of values at an unmeasured location using known data belonging to its neighborhoods. Despite the various interpolation techniques that can be used to help address the situation of limited or missing data, a remaining problem is that the low density of stations has been proven to systemically underestimate extreme values, which are precisely those extreme events that the insurance program is intended to cover. Another challenge with weather insurance is that it does not directly cover other risks such as disease and pests, and may not include other weather risks, such as temperature, wind, snow, hail, etc. All of these additional risks may result in basis risk. Therefore, a main focus of this research is exploring alternative data generating technologies, including satellite/remote sensing imagery.

The Normalized Difference Vegetation Index (NDVI) is commonly used in satellite-based grassland insurance programs, however, there may be limitations (Roumiguié, Jacquin, Sigel, Poilvé, Lepoivre, & Hagolle, 2015a) with this approach. For example, NDVI can be sensitive to sensor effects, lighting conditions, atmospheric conditions and soil effects. This means that it may not be stable over time and in space, making it difficult from an operational point of view in terms of obtaining a sufficient and reliable historical data time series. In addition to NDVI, there are several alternative vegetation indices that may be improvements over NDVI, such as the Green Normalized Difference Vegetation Index (GNDVI), tortking or the Optimized Soil Adjusted Vegetation Index (OSAVI), as examples. As an alternative to vegetation indices, satellite-derived biophysical parameters, such as the Fraction of Absorbed Photosynthetically Active Radiation (fAPAR), the Fraction of Green Cover (fCover), or Leaf Area Index (LAI) provide a physically meaningful measure of the vegetation. These biophysical parameter measures are independent of the sensor, and some research has shown that they may overcome some of the challenges associated with vegetation indices regarding data accuracy and reliability.

1.3. Research Objectives

The overall objective of this research is to develop improved index-based forage insurance products for the Provinces of Alberta and Saskatchewan, to address the current low demand for forage insurance and improve producer risk management. A main focus is on the assessment and development of index-based forage insurance using satellite-derived indices. Two Grassland Production Indices (GPI's) developed by Airbus Defence & Space, which are based on biophysical parameters, including fCover and fAPAR, are examined. In addition, sixteen alternative Forage Production Indices (FPI's) are investigated, which are based on publicly available data. This includes eleven FPI's based on vegetation indices, including various resolutions and data products corresponding to NDVI, EVI, GNDVI, OSAVI, and MSAVI2, as well as two based on biophysical parameters, including LAI and FPAR, and finally three based on ground weather station observations, including heating degree days (HDD), cooling degree days (CDD), and Accumulated Precipitation. Each of the Airbus GPI's and the alternative FPI's are validated against ground truth forage yield data, which includes native and improved pasture data in Alberta, and tame-hay data in Saskatchewan, including alfalfa, grass and alfalfa/grass mix.

1.4. Results

The results of this research show that there are strong correlations in the satellite-based indices compared to the ground truth forage yield data in both Alberta and Saskatchewan. This is compared to the indices constructed from ground weather station variables, which show overall weaker relationships with the yield data in both provinces.

1.4.0.1. Airbus Satellite-Based Grass Production Indices Based on Biophysical Parameters

The two GPI's provided by Airbus Defence & Space show strong correlations in some years with the ground truth forage yield data. For example, as shown in Table 7.3 in Alberta in 2016 the correlation of the Airbus fCover GPI and fAPAR GPI with the ground truth yield data can be as high as 89.86%, and 90.62%, respectively. In Saskatchewan, as shown in Table 7.4 in 2015 the correlation can be as high as 66.87%, and 29.39% for Alfalfa for the Airbus fCover and FAPAR GPI's, respectively. Considering the overall sample (2002 to 2016 for Alberta and 2002 to 2015 for Saskatchewan), however, the correlations with the GPI's and the ground truth data are lower. For example, the average correlation is 68.99% for fCover and 69.16% for fAPAR for Alberta, and for Saskatchewan the average correlation is 48.55% for fCover and 34.33% for fAPAR for Alfalfa.

1.4.0.2. Alternative Satellite-Based Forage Production Indices, Including Vegetation and Biophysical Parameter Indices

Considering the alternative FPI's, strong correlations between the indices and the ground truth forage yields are also observed. For example, Table 7.11 reports the correlations by year for three of the alternative FPI's in Alberta, which shows that for 2016 the correlation of the OSAVI MODIS, NDVI MODIS, and FAPAR MODIS FPI's with the ground truth forage yield data is 86.4%, 87.2%, and 86.0%, respectively. In Saskatchewan, Table 7.14 reports the correlations by year for three of the eleven alternative FPIs, which shows that for 2015 the correlation of the NDVI MODIS, MSAVI2 MODIS, and LAI MODIS FPIs for Alfalfa with the ground truth forage yield data is 60.85, 68.6%, and 36.1%, respectively.

Considering the overall sample (2002 to 2016 for Alberta and 2002 to 2015 for Saskatchewan), however, the correlations with the FPI's and the ground truth data are lower. For example, the overall results for all of the alternative vegetation FPI's in Alberta are shown in Table 7.9, and the alternative biophysical parameter FPI's are shown in Table 7.10. The overall results for all of the alternative vegetation FPI's in Saskatchewan are shown in Table 7.12, and the alternative biophysical parameter FPI's are shown in Table 7.13 The results show that the overall correlations in Alberta can be as high as 61.5% for OSAVI MODIS 500 m - Daily Observation, and 62.0% for FPAR MODIS 500 m - Daily Observation, as examples. In Saskatchewan, the overall correlations for Alfalfa can be as high as 52.7% for MSAVI2 500 m - Daily Observation, and 38.6% for LAI MODIS 500 m - Daily Observation.

In addition to the vegetation and biophysical parameter indices, three alternative FPI's based on ground weather station variables are considered in this report. The three FPI's are based on accumulated precipitation (Precpn), heating degree days (HDD), and cooling degree days (CDD), along with three weighting options to weight the variables across the various months. Overall, the correlations between the weather-station derived FPIs and the ground truth forage yield data are the weakest of the all of the indices considered. In both provinces, precipitation is found to have the highest overall correlation with the ground truth data, which is 12.51% in Alberta and 23.12% in Saskatchewan. It is important to note that the year-to-year variability of the correlations for the weather station-derived FPIs are not stable and can change considerably from one year to the next.

1.5. Recommended Next Research Steps

A main focus of phase two of the research should be on selecting the best performing indices in phase one, and proceeding with further refinement of the model, the design and testing of the insurance product, pricing and actuarial risk assessment, and validation with producers. To accomplish this, the following have been identified as key priorities of the next phase of research. First, it is recommended that more comprehensive ground truth forage yield data is obtained. This includes more detailed information pertaining to measurement dates, and locations, among other considerations. Further, the current analysis focused only on pasture in Alberta and tame-hay in Saskatchewan, therefore, the analysis should be extended to consider tame-hay in Alberta, and pasture in Saskatchewan. To accomplish this, it is recommended that the researchers obtain additional historical data from AFSC and SCIC, as well as other existing forage databases. Further, it is recommended that at least 10 producers from each province are selected and ground-truthing representative of the farm is conducted over at least two growing seasons to aide in designing and validating the forage insurance products. Phase two of the research should also focus on the integration of high-resolution satellite imagery data to augment the medium-resolution satellite imagery data, which was the focus of the current study. In addition, it is recommended that hybrid indices are explored and empirically investigated to study the possible improvement of combining various vegetation and biophysical parameter indices, and ground weather station observations, using advanced statistical approaches, such as machine learning. The unit area of insurance should also be studied to better understand the desired scale of the underlying insurance index from both the perspectives of producers as well as the government crop insurance companies. Finally, phase two of the research should focus on validation of the final insurance product in terms of basis risk, which measures the error in the indemnity computed from the insurance index relative to the actual loss experienced on the farm.

SECTION 2

Background Characteristics of Forage Production

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Forage production is an important part of Canada's agricultural industry, and represents approximately 44% of the farmed area in Canada (primarily in Western Canada). The direct economic value of forage in Alberta and Saskatchewan are approximately $1.6 billion and $747 million, respectively, which includes hay and processed forage production, pasture, forage seed production and silage and green feed. This does not include other indirect and environmental benefits, such as reducing erosion, and improving water quality, the value of which has been estimated as being substantially larger than the direct economic benefits.

Most forage production is consumed by the livestock industry, particularly cattle. Canada has 4.3 million beef cows, of which 82% are in the three Prairie provinces, and 1.4 million dairy cows, of which 13.2% are in the Western Provinces. As a result, forage production in Western Canada is predominantly consumed by beef cattle, with lesser volume for other livestock sectors and end uses. There are opportunities for growth in the Canadian forage industry, including increasing livestock production, and expanding export volumes. Canada is the worlds third largest exporter of forages, with about 10% of the world market.

In 2010 it was estimated that less than 20% of forage was insured in Canada, with poor participation a common challenge for programs that have been implemented in the past in most provinces. However, given the importance of the forage industry to Canadian agriculture and the increasing frequency and intensity of extreme weather occurrences, an insurance policy that captures the risk faced by farmers that is also easy to understand and incorporate into operations, would be a valuable development for the industry.

	Hay	Improved Pasture	Natural Pasture
	Hectares	Hectares	Hectares
Alberta	1,952,600	2,395,944	6,435,825
Saskatchewan	1,821,100	2,057,957	4,816,782

Table 2.1: Land Area in Hectares for Hay (2016), Improved Pasture (2011), and Natural Pasture (2011) in Alberta and Saskatchewan (Government of Canada, Statistics Canada, 2017a, 2017b).

2.1. Forage Production Systems

Most forage in Alberta and Saskatchewan is consumed by beef cattle, and primarily by the cow/calf sector of the industry. The Government of Canada, Statistics Canada (2017c), reports that there are 2.365 million head of cattle in Saskatchewan, including 1.158 million head of beef cows. In Alberta, there are 4.850 million head of cattle, including 1.552 million head of beef cows. These values can be compared to 12.065 million head of cattle in Canada, including 3.833 million head of beef cows. Therefore, Alberta and Saskatchewan together have over 60% of the total Canadian cattle herd, and 70% of the beef cow herd. Table 2.1 shows the land area allocated to hay, improved pasture, and natural pasture for Alberta and Saskatchewan.

There are a number of methods of harvesting forage. Most forage production is harvested through the following means:

1. Grazing: Typical grazing patterns place livestock on pasture from spring until fall. Farmers may also incorporate management practices that would extend the length of time that livestock remain on pasture, including methods such as stockpiling forage, swath grazing, and bale grazing.

2. Dry hay: This refers to forage that is cut and lays in a swath until it is dry enough to wrap into round or square bales. Hay is produced primarily for feed for the winter.

3. Silage: This refers to forage that is cut and then either baled and wrapped in plastic, or else put into a pile, and packed and covered with plastic. In both cases, the moisture level of the forage is higher than for dry hay. This reduces the amount of drying time that is needed for harvesting, and subsequently reduces the risk of swaths experiencing rain prior to being baled into dry hay, which in turn reduces quality. This method of harvest increases in popularity during wet years, when it is difficult to get a long enough window without rain to make good quality dry hay. Silage is also used primarily as a winter feed source for beef cattle producers, although many dairy farms will primarily feed silage, and do so year

round. Some forage will also be produced for forage seed, sod and as feedstock for heat and energy production.

Unlike monoculture crops, forage typically will experience two or three different harvests (often referred to as cuts) over the course of the year, both for hay/silage production and for multiple periods of grazing in a rotational grazing system. Also, the exact form of harvest can vary from one year to the next, and can also be flexible depending on conditions. This is particularly the case for cow/calf and grassing/background beef producers. For example, land that may have been intended for dry hay may be taken off as silage in a wet year. Some fields may have a first cut of hay taken off and then grazed later in the season. Fields initially intended for hay or silage may be grazed in dry years when production is poor.

The timing of the harvest will have an impact on the total volume of forage produced on a piece of land over the course of the year. For example, delaying the timing of taking off a first cut of hay will result in greater production on the initial cut, however, it will also reduce the quality of the hay due to the plants being more mature. The stage of plant growth at the time of harvest is one factor that also has an impact on the amount of subsequent regrowth. High quality forage will tend to be of greatest importance to dairy farmers and exporters. Beef producers that are looking for efficient weight gain (feedlots and grassing/backgrounding operations) prefer good quality forage for the roughage part of their diets. Cow/calf producers are able to use relatively lower quality forage, particularly if other dietary supplements are incorporated into the overall ration.

2.2. Forage Types

Most forage is produced with multiple species grown together, except for alfalfa silage and hay, some timothy hay, and production for seed. This can vary considerably, and as much within a region as across the different regions of Western Canada. There is some variability by region due to the local concentration of livestock production systems and regional climactic differences, particularly for native pastures. However, tame hay and improved pasture share many common species across all Prairie regions. For example, certain species of grasses and legumes perform relatively better under wetter or drier conditions, and therefore, they are grown on the same operation to reflect the varying conditions and soil types. Some species may also show more growth earlier or later in the growing season. By growing multiple species together, the producer can increase the overall forage production on a piece of land by mixing together species that exhibit their peak production windows during different periods of the season. Thus, seed mixes may include up to 8 or more different species of a grass and legume mix, which would include several species out of dozens of different grass types and 8 commonly used legumes. Another consideration is whether the forage is likely to be used primarily for making hay, grazing or both.

2.3. Forage Production Risks

Whereas some producers consider forage as a crop to sell to others, most forage is produced with the intent of securing a feed supply for their own livestock. Feed costs are typically the single largest cost for beef producers. The proportion of total costs vary by l;production system, including hay and pasture for cow/calf producers, and pasture for grassing/background operations. The Saskatchewan Forage Council (2011) estimates that feeding and grazing systems comprise approximately 60 to 70% of the total production cost of cow/calf operations in Western Canada. As a result, this is a key area of focus as producers look to manage costs and risk.

In cases where there is a production shortfall, and particularly in the absence of forage insurance, farmers can consider several different strategies to fill this feed supply gap. These strategies can include buying additional hay, sourcing other feedstuffs, reducing herd size or carrying over additional forage supplies from one year to the next. While livestock farmers have a number of possible methods for managing forage production shortfalls, the consequences can still be quite severe. For example, purchasing hay or other feedstuffs can be costly and volatile as prices increase when supplies are limited. In addition, forage markets are typically less transparent, and they also are not as well established as most other cash crops. This creates further challenges in sourcing and valuing replacement supplies. Further, transportation costs for hay are typically high because of its bulky nature, limiting the volume that can be shipped efficiently. Liquidated herds eventually need to be replaced if the operation is to continue as a viable entity, potentially at higher prices than what was received when animals were sold under duress. There are also operational considerations when bringing different animals and genetics back onto a farm. Carrying excess hay inventories into the following year may be an inefficient use of working capital, particularly when accounting for the additional shrinkage when holding stocks through to the following winter. Therefore, while most forage producers have alternative methods to help address a production shortfall, these alternatives may still be very costly and considerably less effective than an appropriate insurance policy.

2.4. Forage Insurance Considerations

There are several factors that make insuring forage production different from traditional insurance for annual crops. Some of these include:

- Aside from those farmers that sell forage as a cash crop, most producers would use insurance indemnity payments towards replacing lost production and feedstuff inputs for their livestock. This compares to traditional crop insurance for annual monoculture crops, where payments would go towards recovering sunk input costs. In other words, indemnity payouts from a forage insurance policy would need to compensate producers in a manner to sufficiently offset the cost of replacing the forage production that was lost.

- Given that a large portion of forage production is consumed on the operation where it is produced, there are limited statistics available in regards to the actual volume of production, quality, or measurement of market value. This makes it difficult to measure the actual value of forage production that is lost, both in aggregate and for any individual operation.
- Forages are perennial crops, with sunk costs typically amortized over a 4 to 7 year window, compared to every year for annual crops.
- Forage markets are typically less transparent with limited price information compared to most annual crops. Production is either used on the operation or sold through a less formal supply chain.

Yields for all forage crops will vary from one operation to the next based on management practices, local soil types, investment in inputs, and other factors. However, there may be more variables affecting the production on a given forage field or pasture than what one would typically face in traditional crop insurance for monoculture annual crops. Some of these factors include:

- Yields on most forage species decline over time. It is typical to see initial high yields in response to high available nutrient levels due to annual cropping prior to forage seeding, which then erode in future years as nutrient levels decline and plants move past their peak production years.
- The forage mix will vary with each field. This mix will also change over time as some species become more dominant, or have different production levels across their lifespan.
- Individual species will respond differently to varying rainfall amounts and other weather conditions, creating additional variation from one field to the next, and from one year to the next depending on the species mix.
- The method and timing of harvest can vary considerably from one farm to the next (grazing, dry hay, silage, number of cuts), depending on the specific end use and other operational considerations. Producers are also continuing to evolve their grazing and forage management practices.

2.5. Forage Production Regions

An important consideration in examining vegetation growth in Alberta and Saskatchewan may be soil type and ecozone. There is considerable geographical overlap between soil types and ecozones, however, the econzones reflect variation not just in soil type, but also plant species, temperature, rainfall patterns, wind, heat units, length of growing season and other factors. In general, Gray soil zones can be found north in the prairie provinces in Canada, followed by a thin Dark grey soil zone band. The Black soil zone can be found mid-province, and in the province of Saskatchewan extending to the south-east border. The Dark Brown soil zone is found below the Black soil zone, and extends to the south-west border in Alberta and the south-east border of Saskatchewan. Finally, the Brown soil zone is found in the south parts of each province.

In terms of ecozones, Southeast Alberta and South central Saskatchewan have Mixed Grassland, which corresponds to the Brown soil zone. Central Alberta is comprised of Moist Mixed Grassland and Aspen Fescue, corresponding to Dark Brown and Black soil zones, respectively. Fescue Grassland is found in Southwestern Alberta, which is also the Dark Brown soil zone. Finally, Central Saskatchewan is Moist Mixed Grassland, corresponding to the Black soil zone. For a visual representation of the ecozones in the prairie provinces in Canada, see Figure 2.1.

The map below, produced by Airbus in this first phase of the project, shows the percentage of grassland per each 6km by 6km unit area and is an indicator of the exposure spread over the provinces of Alberta and Saskatchewan.

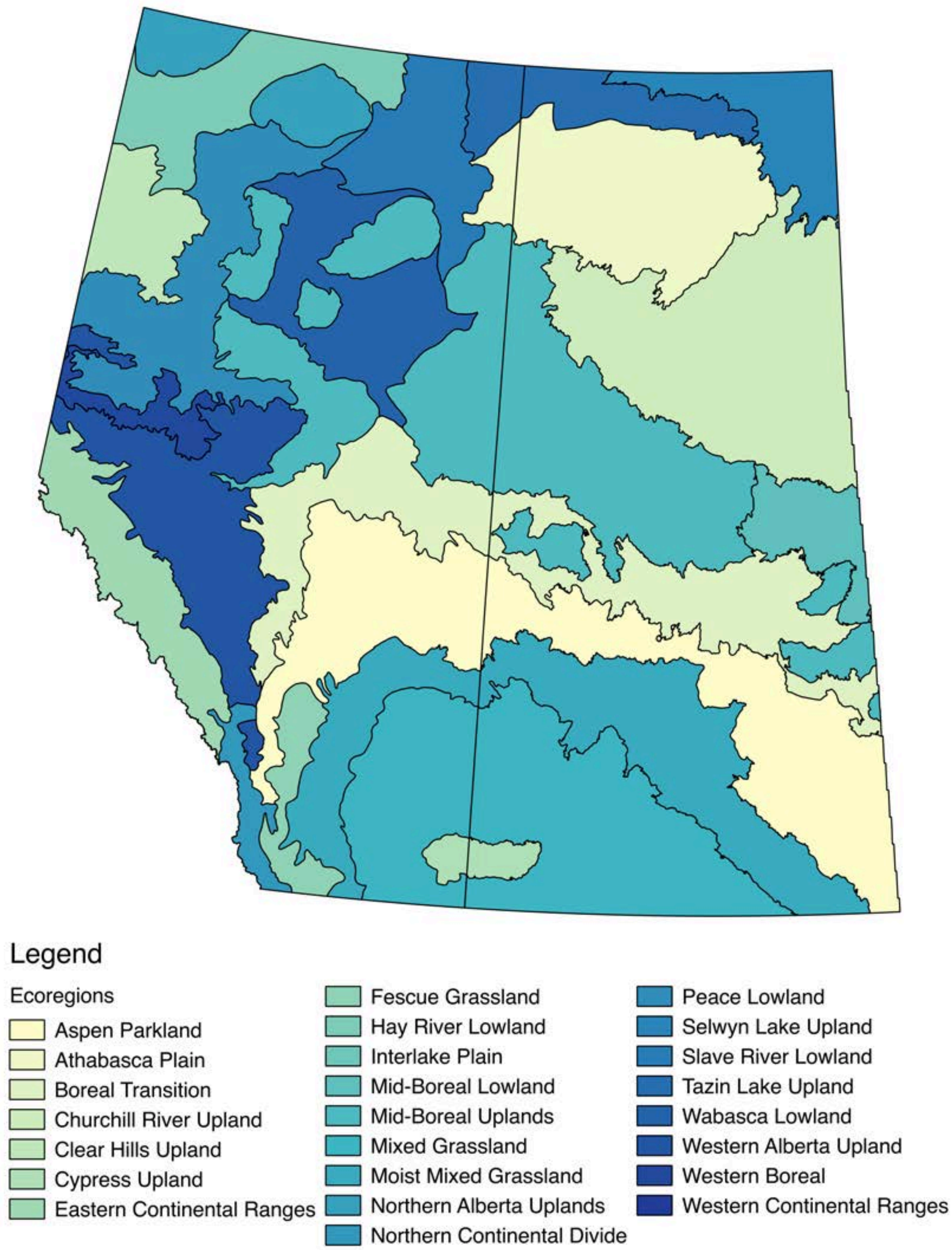

Figure 2.1: Ecozones of Canada

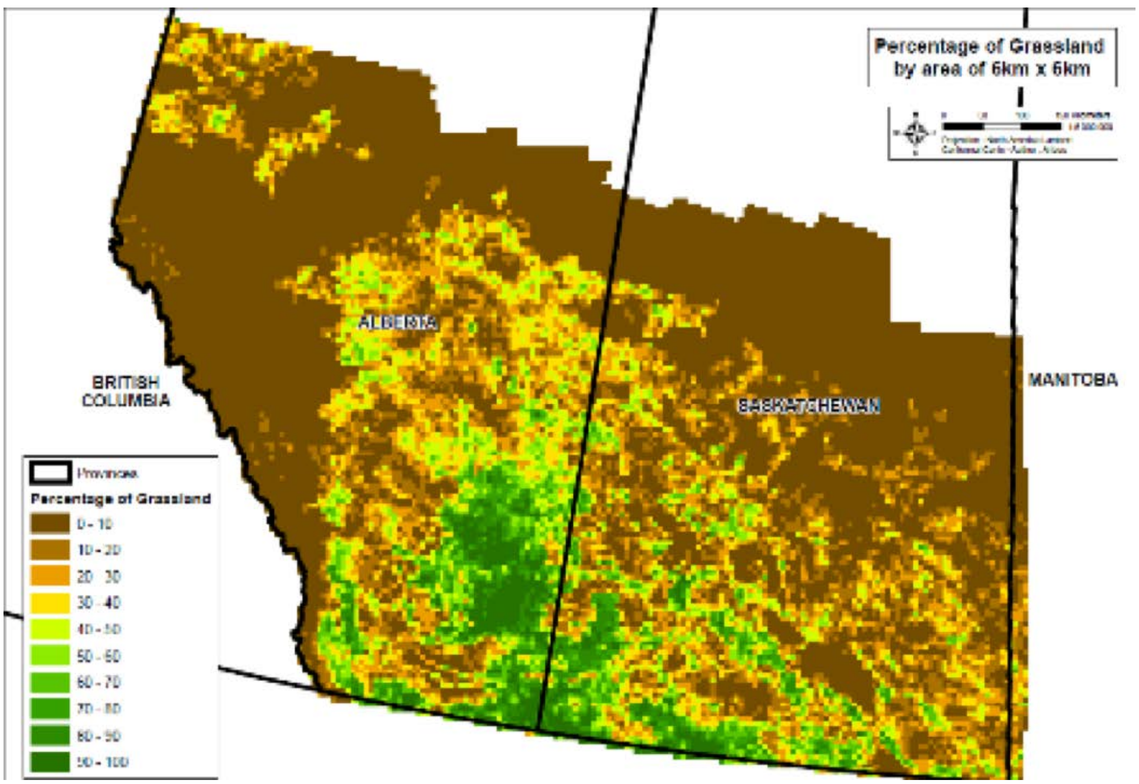

Figure 2.2: Percentage of grassland per each 6km by 6km unit area for Alberta and Saskatchewan

SECTION 3

Data Sources and Descriptions

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In this section, an overview of the sources of data used in this project is provided. This includes the data used to construct the various Airbus Grassland Production Indices (GPI's), the alternative Forage Production Indices (FPI's), as well as the ground truth forage yield data used to validate the GPI's and FPI's. The data used to construct the various GPI's and FPI's includes low, medium and high resolution satellite imagery, as well as ground weather station data. In order to conduct a preliminary feasibility assessment of the various GPI's and FPI's, ground truth forage yield data is used. For the province of Alberta this corresponds to improved and native pasture clip sites, and for Saskatchewan this corresponds to yield data recorded for insurance purposes for the current operational tame-hay insurance program, which includes alfalfa, grass and alfalfa/grass mix. Included in the discussion of the data are possible limitations, which are important considerations when interpreting the results, as well as for planning the next phase of the research and development.

3.1. Satellite Imagery Data

The various GPI's and FPI's developed in this phase of the research use low resolution (LR), medium resolution (MR), and high resolution (HR) satellite imagery. The Airbus GPI's are based on MR satellite imagery, and HR satellite imagery is also used for validation purposes. The satellite-based FPI's use a combination of LR and MR satellite imagery. Each of the satellite imagery data sources are described next, and the details of the Airbus GPI's, and the alternative FPI's, are provided in the following section of the report.

3.1.1. Low Resolution Satellite Imagery

Low resolution (LR) satellite imagery at 1-kilometer resolution from the Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) series of Earth observation (EO) satellites is obtained from Statistics Canada (Statistics Canada, 2017). The time-series begins in 2000 through 2016 to match the available ground-truth forage yield data.

The LR data is used to calculate one of the alternative FPI's considered in this research, which is referred to as the NDVI AVHRR 1 km FPI. The current forage pasture insurance program in Alberta is also based on a NDVI AVHRR 1 km index. Therefore, this FPI serves as an interesting comparison in this research. The NDVI AVHRR 1 km index is only computed for the province of Alberta, as Saskatchewan does not use this index for insurance purposes.

3.1.2. Medium Resolution Satellite Imagery

The medium resolution (MR) satellite imagery data used in this research consists of a time series of images from 2000 to 2016 acquired by the Medium Resolution Imaging Spectroradiometer (MODIS) sensors. The MODIS sensors are onboard the multi-national Terra and Aqua scientific research satellites, operated by the National Aeronautics and Space Administration (NASA). The Aqua/Terra MODIS sensor data are publicly available online, and are distributed as data products through the Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC), part of the Terrestrial Information Systems Laboratory at NASA Goddard Space Flight Center in Greenbelt, MD, United States (NASA, 2017a). The resolution is typically between 250 m and 500 m depending on the band.

Medium resolution remote sensing data may also include data acquired by sensors onboard the Sentinel-3 satellite constellation, developed by the European Space Agency (ESA) as part of the Copernicus Programme. Select Sentinel-3 data products are also publicly available online from LADDS DAAC (NASA, 2017a).

The MR data is used to calculate the two Airbus GPI's, which are based on a resolution of 300 m and aggregated to a 6 km by 6 km grid. In addition, several alternative FPI's are computed from the MR imagery data, including NDVI, GNDVI and MSAVI2, from MODIS at a resolution of 250 m, as well as LAI and FPAR, from MODIS at 500 m resolution.

3.1.3. High Resolution Remote Sensing Data

The high resolution (HR) satellite imagery data used in this research is obtained from the SPOT-6/7, and Sentinel-2 sensors. The resolution is typically between 5 m and 60 m depending on the band/sensor. The HR satellite imagery is used only for validation purposes for the two Airbus GPI's.

3.2. Weather Station Data

Three of the alternative FPI's developed in this research are based on ground weather station data. The Alberta weather station data is downloaded from Alberta Agriculture and Forestry at the following webpage: $http : //agriculture.alberta.ca/acis/alberta - weather - data - viewer.jsp$. The Saskatchewan weather station data is obtained from Saskatchewan Crop Insurance Corporation (SCIC), which was provided by Environment Canada. The coordinates for the weather stations in both provinces are downloaded from Government of Canada at the following webpage: $http : //climate.weather.gc.ca/historical_data/search_historic_data_e.html$.

The weather variables considered in this report include daily temperature and daily precipitation. From this, heating degree days (HDD) and cooling degree days (CDD), as well as accumulated precipitation (AccPcpn) are calculated, each serving as one of the alternative FPI's.

3.3. Ground Truth Forage Yield Data

As part of the feasibility assessment of this project, the Airbus GPI's and the alternative FPI's are validated using ground truth forage yield data. The term ground truth originates from the geological and earth sciences disciplines to describe the validation of data by going out in the field and checking on the ground. This term has been adopted in other disciplines to explain the idea of data that is known to be correct. In this sub section, a description of the ground truth forage yield data in the provinces of Alberta and Saskatchewan are discussed next.

3.3.1. Alberta Ground Truth Forage Yield Data

In Alberta there are three main insurance programs that provide coverage for hay and pasture producers. This includes an 1) Individual Farm Loss-Adjusted Hay program, as well as two insurance alternatives for Pasture, including a 2) Moisture Deficiency Insurance (MDI) program and a 3) Satellite Yield (SAT) program. The MDI program is an area-based index program that uses weather station and spring soil moisture information. The SAT program is also an area-based index program, and uses NDVI data at the township level. Producers can be insured under either the MDI or SAT program.

The ground truth forage yield data used in Alberta corresponds to the SAT program. Typically index-based insurance programs face challenges in terms of validation data.

This is because payments to producers are based on the index rather than farm-level loss adjusting, therefore, actual farm-level historical forage yield data is often not tracked. However, in the case of Alberta, a network of 99 cage sites (clip locations) are available, and each site has several years of historical data from 2002 to 2016. The clip sites are used to monitor and estimate pasture plant growth, and are used to supplement the SAT information to revise payment rates.

In addition to the pasture clip sites, Agriculture Financial Services Corporation (AFSC) also maintains an insurance database corresponding to the individual Hay Program with several years of historical records. AFSC contacted 10 producers that participate in this program, who agreed to share their loss data, and this data will be analyzed in the next phase of the research.

3.3.1.1. Network of Cage Sites (Corresponding to SAT Program)

This data corresponds to non-crop insurance data for pasture production for an extensive network of 99 cage sites, which was provided by AFSC. Figure 3.1 provides an overview of the network of cage sites around the province. Most samples correspond to the South and South East part of Alberta, which is consistent with the current area of enrollment in the SAT program. It is estimated that there are approximately 24 million acres of pasture in the province of Alberta, and the clip site areas represent about 8 million acres. Most of these clip locations are for native pasture, however, some observations are for improved pasture. Native pastures can be described as simple grazing environments that usually are dominated by native grasses and contain many other native herbs and shrubs. Management of native pastures are typically in the form of grazing management, and can also be used for hay production as a complement. In contrast, improved pastures are regularly seeded with specific species (crop mix), usually grasses in combination with legumes. Improved pastures are typically more productive than the local native pastures, and once sown they require more management in terms of fertilization, harvest and in some cases irrigation.

From the total 99 locations in the clip network in Alberta, 25 representative locations were chosen for this feasibility assessment phase of the research, which included historical observations from 2002 to 2016. Test sites were selected by AFSC. This included 20 native pasture sites, and five improved pasture sites. For each location there are six sites, with two cages per site. Currently, clipping at each site is done twice in the growing season (June and August). For clarity, the first clip corresponds to growth from season start until June, and the second clip corresponds to growth from season start until August (i.e. not regrowth from June to August). For the analysis in this project, the yield measurement at each of the six sites are averaged to obtain an average area yield for that location for that measurement period, which is then compared to the Airbus GPI's or alternative FPI's. The polygon layer for the Alberta test sites were manually classified by Airbus Defence & Space to include only acres that

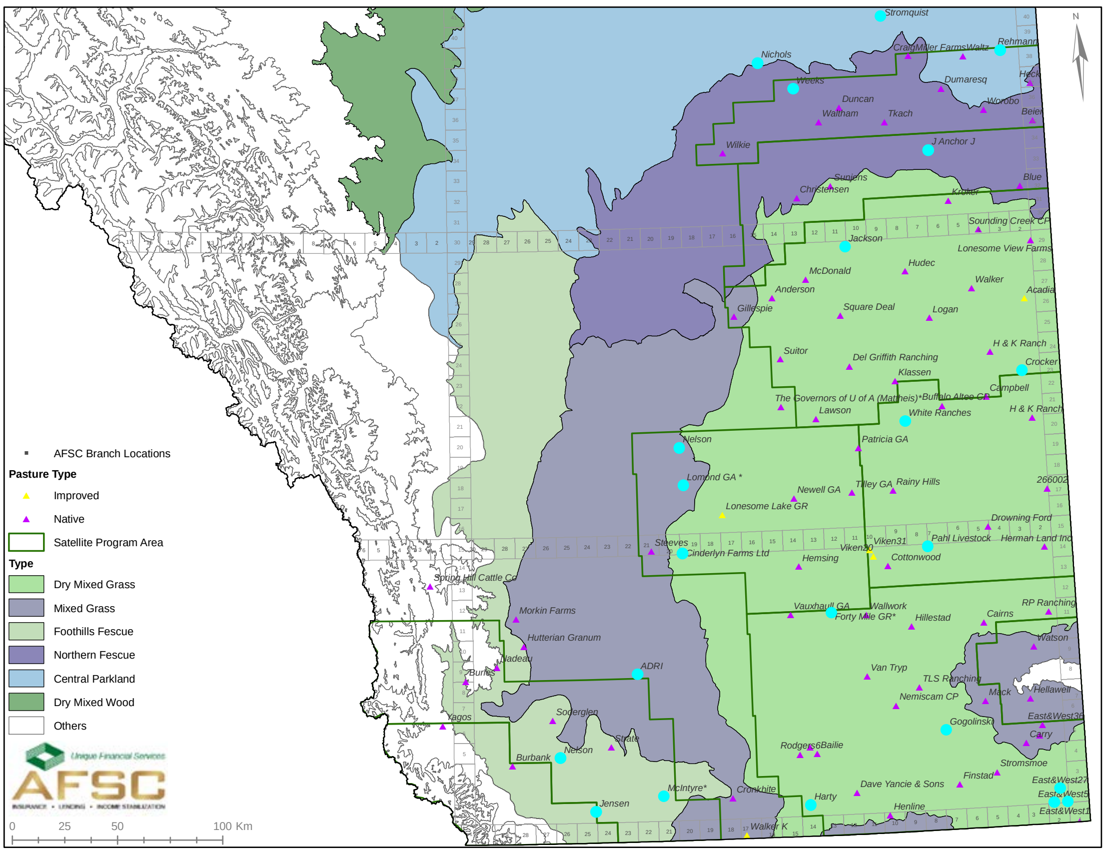

Figure 3.1: Network of Cage Sites in Alberta.

were determined to produce forage crops (to ensure that only the area representing the forage crop is sampled from the index for the Airbus GPI's and alternative FPI's). This manual classification is possible given the relatively small number of test sites and the consistency of the geographic locations from year to year. This is compared to the Saskatchewan data set, which is discussed next, in which there are too many test sites to perform manual classification, therefore, an automated classification approach is adopted.

Details regarding the data recorded at each clip site are outlined below.

1. Latitude and Longitude: For each cage of the 25 locations the corresponding coordinates are recorded (latitude and longitude).
2. Yield is measured as follows:
    (a) 1 m by 0.5 m clip frame area and clipped at 1/4 inch (close to ground) for six cages at many of the 25 clip sites.
    (b) Live clipped grass and forbs (which refer to any herb that is not a grass or grasslike) sorted in field or office and dried to constant dry weight. The cage grass and forb weight is converted from the measurement unit of g/m^2 to a unit of $lbs/acre$ (dry weights of grass and forbs each multiplied by a factor of 17.84 to get grass and forbs weights in $lbs/acre$ and total (grass + forbs) in $lbs/acre$).
    (c) Two measurements are taken over the growing season in the months of June and August for the years 2012 to 2016, and four measurements are taken over the growing season in the months of May, June, July and August for the years 2011 and prior.
3. Grass Type: for each site, the grass type is recorded, including Dry Mixed Grass, Mixed Grass, Central Parkland, Foothills Fescue and Northern Fescue.

3.3.1.2. Limitations of the Alberta Data

Preference would be to utilize the dataset in its entirety, however, data cleaning is necessary for a number of different reasons. Firstly, test sites are not necessarily consistent over the years. Some clipping sites drop in and out of the dataset across the years, and this means that sites which are present for one year, may not be present in the sample for the next. This introduces noise into the analysis since we do not have a consistent sample over the observation period. For the analysis in this paper, the whole dataset is used, however, samples are removed that have limited data observations in order to minimize distortion. In addition, there can be large variability in the pasture production measured at each clipping site. This may be explained by the fact that each cage is a relatively small area that measures 1m by 1m. To limit the noise created by this variability, especially since each cage is significantly smaller than the scale of the index, the data is further cleaned.

Therefore, the data filtering process begins with the entire ground truth yield dataset, consisting of measurements from 25 test sites, each of which has six clipping cages with distinct locations identified by their longitude and latitude. Next, each cage in the dataset is linked to the corresponding index grid cell. For the Airbus GPI's, each grid cell is 6 km by 6 km (compared to the cage size of 1 m by 0.5 m), and this means that one or more cages may be mapped to the same grid cell. To smooth noise coming from the ground data, the cage yield per grid cell is averaged, and any grid cells that contain less than three cages are excluded. For the alternative FPI's considered in this paper all cage yield measurements are averaged, and a polygon layer is created that corresponds to the forage at the cage site locations. The polygon layer is used to sample the underlying alternative FPI, which is at a spatial resolution of either 250 m or 500 m, depending on the FPI.

In addition to the data cleaning discussed above, there are also several observations about the ground truth forage yield data. First, pasture production in Alberta is highly volatile across the province. This volatility is due to a number of different factors, such as the location of the farm (e.g. altitude, latitude, soil, local weather, etc.), the type of pasture (native, improved), as well as differences due to farm management (e.g. applying nitrogen, carry-over management, etc.). Second, in some specific cases, known events do not seem to be captured by the clipping data. This could be due to clipping location or to clipping protocol (and especially the date at which the measurement was made). It also should be noted that ground truth forage yields are divided into two measurements, including grass and forbs, where the sum of the two gives the total pasture production. Since the indices constructed in this study provide an estimate of total pasture production, the sum of grass and forbs is considered as a single yield value for each cage.

3.3.2. Saskatchewan Ground Truth Forage Yield Data

In Saskatchewan there are two main insurance programs for forage producers, including 1) Individual Farm Loss-Adjusted Tame Hay and 2) a Weather-Based Forage Rainfall Insurance Program (FRIP) primarily targeted towards pasture. The Tame Hay program guarantees a forage yield based on the shortfall between the yield guarantee and the actual yield produced, paid at the insured price for the crop. Coverage is based on a producers individual growing experience rather than an area average. The FRIP is available on native and tame grazing acres, and protects against the risk of seasonal precipitation falling below the long-term average. This is the only insurance program available for native forages, and provincial and federal grazing pastures are excluded. FRIP is an index-based insurance program, and not an individual insurance program. Insurance payouts are based on an underlying weather index that uses precipitation from selected weather stations as the only means of determining a claim. This means that farm-level loss adjusting is not required. Claims do not have to be filed, and instead they are automatically calculated at the end of the season based strictly upon weather station data.

The ground truth forage yield data used in Saskatchewan for this phase of the research corresponds to the individual farm-loss adjusted Tame Hay program, and this dataset was provided by SCIC. This program provides yield-loss coverage for established tame perennial crops grown for forage. The analysis at this stage of the research is limited to the individual farm-loss adjusted Tame Hay program data only, and does not include pasture yield data. This is because the FRIP is an index-based product, and actual farm-level historical forage yield data is not tracked. The next phase of the research plans to conduct grass cutting experiments for pasture in addition to tame hay, which would allow a more comprehensive analysis.

The Tame Hay insurance program covers three species, including alfalfa, alfalfa/grass and grass. Forages typically experience two or three different harvests (i.e. cuts) over the course of the growing season. Weather conditions often influence the exact form of harvest from year to year, in order to maximize volume and quality. The various number of forage cuts will provide a different number of observations throughout the growing season, with a single cut giving single observations, while two cuts would give two observations, for example. In terms of designing an insurance policy, it may be desirable to have an insurance policy with multiple triggers, based on multiple cuts.

The farm-level yield-loss dataset that was provided by SCIC covers the period from 2000 to 2015. Yield data is self-reported, therefore, SCIC has an audit process. The dataset includes the following information:

- Insured Units: Three different insured units, including Alfalfa (code 641), Alfalfa/Grass (code 642) and Grass (code 643).
- Age of Stand: categorized as less than ($<$) 8 years and more than ($>$) 8 years.
- Legal Land Description (LLD): Defined by the Dominion Land Survey, which began in Canada in 1871. Locations are defined in terms of the Meridian, Range, and Township. Each township consists of 36 Sections and is approximately 6 miles square. Each Section is then made up of 4 Quarter Sections, described as the NE, NW, SE and SW Quarters. Each Quarter Section is approximately 160 acres (65 hectares).
- Latitude and Longitude: corresponding coordinates (latitude and longitude) for the centroid of the Quarter Section is recorded.
- Soil Zone: classified as Black/Grey, Dark Brown or Brown.
- Forage Zone: Classified in a range from 1 through 17, representing various Risk Zones as determined by empirical analysis by SCIC.

- Acres: total number of acres produced over the insured area.
- Long-Term Individual Yield (LTIY): categorized the same as age of stand as either less than ($<$) 8 years or greater than ($>$) 8 years. The LTIY is based on approximately 10 years of historical experience.
- Production Output: reported in kg of production over the total acres for the insured area.
- Production Output per Acre: reported as the average kg per $acre$ of production for the total acres of the insured area.

The total dataset includes 4,754 unique producer id's. However, the data was filtered to meet a number of important criteria, which are outlined below.

- Entries with missing data are removed.
- Observations with yields recorded as "0" are also removed because this corresponds to a total insurance payout (write-off). In the case of a total insurance payout, it does not necessarily mean that the yield was zero.
- Farm id's with the same reported yield per acre for different forage species on the same Legal Land Description (LLD), which corresponds to a Quarter Section, are also removed. For the current insurance program the data is recorded in this way, however, at this stage of the research we are interested in understanding the behaviour of the indices relative to the specific forage species (which cannot be determined when the yields of different forage species are averaged over the LLD).
- Only LLD's with a minimum number of acres within the 160 acre Quarter Section are retained. Table 3.1 shows the criteria utilized, which considers different thresholds for each of the three species (i.e. grass, alfalfa, and grass/alfalfa mix), as well as for the various years. This is because we do not have the information regarding exactly where on the Quarter Section the non-forage acres are. It is important that the reflectance signal (from the satellite imagery data) within the LLD is primarily forage. This is also important for the Airbus GPI's that are constructed using high resolution (HR) satellite imagery data.
- The data is also filtered by type of forage, which includes four categories. The first is alfalfa, the second is alfalfa/grass, the third is grass and the fourth is all combined. In the case of combined, then we do not apply the filter for the scenario where the same reported yield per acre for different forage species are reported on the same LLD.

- A distance cut-off algorithm that only considers LLD's that are close in geographical proximity to each other is applied. In this phase of the research, a cut-off distance of 1000 m is utilized. The reason this is done is because the reported forage yield per LLD is an average value of the total forage yield for all LLD's for the given producer (i.e. farmer id). Therefore, this filter helps to ensure that the forage yield values that are compared to the Airbus GPI's or alternative FPI's are representative of a specific geographic area. This is compared to the situation where the LLD's can be located a considerable distance from one another, therefore, the average yield per acre may be potentially biased due to spatial differences (i.e. soil quality, weather conditions, etc.).

Of the remaining LLD's in the filtered data set, the centroid location (latitude, longitude) is buffered to create a square polygon with an area that is approximately 160 acres (representing a Quarter Section). The polygon is then used to sample the gridded index (GPI, FPI) layer.

3.3.2.1. Limitations of the Saskatchewan Data

As with the ground truth data in Alberta, there are also several limitations with the ground truth data in Saskatchewan. First, low yields are not always reported and may be recorded as zero values, as this corresponds to a total insurance payout (write-off). This means it is difficult to track the actual yield in very bad years. A second difficulty is in regards to the location of the ground data measurements. The exact location of the ground truth forage yield data is not known precisely and this makes it difficult to compare to the appropriate index value. With this dataset, only the location of the Quarter Section is known, of which a farmer may only farm a small area. This is especially a problem for some of the higher resolution indices, where irrelevant locations could be contributing to the total index value. This is partly dealt with by only considering producers whose acreage exceeds a certain number in each LLD, but, it means that a large number of data are excluded in the validation dataset. A third difficulty pertains to the timing of when the cuts are made, as only the final aggregate yield value is recorded at harvest, and this makes it difficult to compare to the index. Further, yields are measured at different times, by different people (with occasional audits by SCIC). There could be situations where reported yields are underestimated or overestimated. Also, yields may not be measured precisely, and their may be inconsistencies in how yields are measured and recorded from one producer to the next. In addition, some forage may be used on-farm without being reported.

Table 3.1: Minimum Number of Acres Used in Algorithm for Data Selection in Saskatchewan by Crop Species and Year

	Year	Producers	Species	Minimum.Area.per.Quarter.Section..Acres.
1	2002	41	Alfalfa	140
2	2003	38	Alfalfa	140
3	2004	44	Alfalfa	140
4	2005	28	Alfalfa	140
5	2006	26	Alfalfa	140
6	2007	16	Alfalfa	140
7	2008	17	Alfalfa	140
8	2009	18	Alfalfa	140
9	2010	20	Alfalfa	140
10	2011	17	Alfalfa	140
11	2012	21	Alfalfa	130
12	2013	16	Alfalfa	130
13	2014	19	Alfalfa	120
14	2015	11	Alfalfa	120
15	2002	33	Alfalfa/Grass	140
16	2003	32	Alfalfa/Grass	140
17	2004	28	Alfalfa/Grass	140
18	2005	27	Alfalfa/Grass	140
19	2006	24	Alfalfa/Grass	140
20	2007	26	Alfalfa/Grass	140
21	2008	22	Alfalfa/Grass	140
22	2009	25	Alfalfa/Grass	140
23	2010	19	Alfalfa/Grass	140
24	2011	20	Alfalfa/Grass	140
25	2012	23	Alfalfa/Grass	130
26	2013	23	Alfalfa/Grass	130
27	2014	14	Alfalfa/Grass	130
28	2015	11	Alfalfa/Grass	130
29	2002	26	Grass	100
30	2003	26	Grass	100
31	2004	21	Grass	100
32	2005	18	Grass	100
33	2006	19	Grass	100
34	2007	21	Grass	100
35	2008	18	Grass	100
36	2009	14	Grass	100
37	2010	16	Grass	100
38	2011	19	Grass	100
39	2012	15	Grass	100
40	2013	14	Grass	100
41	2014	11	Grass	100
42	2015	9	Grass	100

SECTION 4

A Review of Remote Sensing Methods for Estimating Yield

Dr. Milton Boyd, Dr. Brock Porth, Dr. Lysa Porth, Dr. Ken Seng Tan

The development of remote sensing offers technical support for the insurance industry to detect and assess losses, providing new opportunities to design innovative and improved insurance policies (Rojas, Vrieling, & Rembold, 2011). For forage production, remote sensing is useful because it is difficult to physically measure on the ground, due to continuous livestock consumption, significant variability in plant species as well as physical geography, and grazing management strategies. Moreover, traditional indemnity-based insurance, such as multi-peril crop insurance (MPCI), is vulnerable to information asymmetry, including moral hazard and adverse selection (Miranda, 1991).

Given these challenges, index-based insurance may be a particularly suitable alternative for the development of forage insurance. As described previously, index insurance provides payouts based on an external indicator, or index, which triggers a payment to all producers within a geographically defined space. This is compared to traditional insurance where payments are based on the actual assessed loss at the farm. In order for index insurance to be successful, and accepted by the producer and insurer, it is important that the index has a sufficiently strong relationship with the event being insured.

This section reviews and summarizes the use of satellite-based remote sensing methods for estimating crop yields and forage yields, including the main methods such as NDVI and biophysical variables.

Historically, NDVI has been a popular vegetation index used to estimate yield. Over time, NDVI has been modified and new names have been adopted for these improved NDVI versions. In more recent years, a biophysical variable approach has emerged for estimating yield. This approach appears to be superior to NDVI and related measures, according to a number of researchers (Baret & Weiss, 2010; Camacho & Torralba, 2011; Roumiguié, Jacquin, Sigel, Poilvé, Lepoivre, & Hagolle, 2015b).

4.1. Background

Satellite based crop yield estimation has been improving over time, and will continue to improve rapidly with advances in satellite technology. Satellites continue to improve with more bands, better sensors, and better resolution. Also, software and image processing capability continues to improve, along with more computing power (e.g. cloud computing), and more data storage is available to deal with big data at lower cost. As well, advances in machine learning, such as neural networks, can improve the computing and processing capability.

For yield estimation accuracy, a popular measure of accuracy is the coefficient of variation, which is commonly referred to as R squared, R^2. This is the ratio of the explained variance to the total variance, and it has bounds between zero and one. R^2 can measure the relationship between a vegetation index NDVI crop yield estimate and the crop yield on the ground, for example. The higher the R^2 level, the stronger the relationship is between the NDVI vegetation index crop yield estimate, and the crop yield on the ground. In general, researchers using satellite based remote sensing such as NDVI, and other methods such as biophysical variables, have typically shown R^2 of roughly around the range of 0.60 level to 0.80 level, though some may be higher or lower. For example, Roumiguié, Jacquin, Sigel, Poilvé, Lepoivre, and Hagolle (2015b) results showed thirty nine R^2 values, ranging from 0.62 to 0.90. The strength of the relationship, or R^2 value may depend on: the type of vegetation index or production index, the particular methods used, the satellite technology, resolution, software and image processing technology, agronomic and weather conditions, type of crop, soil type, ground data measurement accuracy, aggregation levels, and many other factors. In general, as satellite technology and information technology continues to improve, satellite based estimation of crop yield will also continue to improve.

4.2. NDVI (Normalized Difference Vegetation Index) for Estimating Yield

NDVI refers to Normalized Difference Vegetation Index (Pineiro, Oesterheld, & Paruelo, 2006). It is a satellite based remote sensing approach, referred to as a vegetation index, that can be used to make vegetation estimates (e.g. forage yield estimates). It is described below, and is the most common satellite based approach for estimating yield. NDVI can be thought of as a method which estimates biomass and plant density, and these in effect are estimates of yield. NDVI became very popular in the 1980's and 1990's and has since been expanded upon and improved (Mulla, 2013). NDVI is computed from visible (VIS) light and near-infrared (NIR) light, reflected by vegetation (NASA, 2017c), and also is sometimes referred to as a canopy reflectance measure. The VIS light used in the NDVI formula is most often Red (R). Though sometimes Green (G) light is used instead of Red (R), as mentioned later below, and this is a more recent development called GNDVI. The formula for NDVI is:

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \tag{4.1}$$

where NIR refers to near infrared and VIS refers to visible light. Higher NDVI indicates greener vegetation (higher yield), whereas lower NDVI indicates less green vegetation (lower yield). The NDVI index is based on the normalized difference between NIR and VIS. NDVI ranges from -1 to 1. It is commonly well above zero for moderate vegetation, and nearer to 1 for very dense vegetation. NDVI will be typically slightly above zero for no vegetation (bare soil), and may be negative for clouds, snow, or water, which have high reflectance.

More dense vegetation absorbs most of the visible light (VIS) that strikes it, and reflects a large part of the near-infrared light (NIR). Less dense vegetation reflects more visible light (VIS) and less near-infrared light (NIR). Therefore, the relatively higher amount of near infrared light (NIR) that is reflected, compared to the amount of visible light (VIS) that is reflected, the more dense the vegetation, and the higher the NDVI. In summary, NDVI is defined as near-infrared light (NIR) minus visible light (VIS), divided by near-infrared light (NIR) plus visible light (VIS). Light is also often referred to as solar radiation in remote sensing literature.

4.3. More Recent Improved Versions of NDVI for Estimating Yield

Due to a number of challenges regarding NDVI, including soil reflectance, numerous other improved methods building upon NDVI have been developed. These have resulted in more recent NDVI related versions that can be used for estimating yield (Mulla, 2013), and many of these were evaluated for effectiveness (Sripada, J.P., Dellinger, & Beegle, 2008). These more recent improved NDVI versions include adding the Green band (G), in addition to NIR and Red (R) bands, as adding the Green band (G) focuses on pigments other than chlorophyll absorbing radiation. This approach has resulted in the following methods:

$$NG = G(NIR + R + G), \tag{4.2}$$

$$NR = \frac{R}{(NIR + R + G)}, \tag{4.3}$$

$$GRVI = \frac{NIR}{G}, \tag{4.4}$$

$$GDVI = NIR - G, \tag{4.5}$$

$$GNDVI = \frac{(NIR - G)}{(NIR + G)}. \tag{4.6}$$

The next group of NDVI improvements below were developed primarily to compensate for the effects of soil reflectance, given for example, that NDVI will tend to produce too high a value and overestimate crop yield when soil contains more water. Formulas in this group include a constant number added to the formula in some cases, as well as the Green (G) band in some cases. For the last measure below in Equation 4.12, EVI (Enhanced Vegetation Index), a Blue band (B) has also been added (Huete, 2006). EVI attempts to use the Blue band (B) to correct for atmosphere, as the aerosol influences the Red band (R). EVI also attempts to address the problem of underestimation of yield, for high yield cases. As well, compared to NDVI, EVI is less sensitive to chlorophyll, and more sensitive to canopy structure variations, such as Leaf Area Index (LAI). The following are some of the various NDVI related vegetation indices that address or compensate for soil reflectance issues:

$$SAVI = 1.5\left[\frac{(NIR - R)}{(NIR + R + 0.5)}\right], \tag{4.7}$$

$$GSAVI = 1.5\left[\frac{(NIR - G)}{(NIR + G + 0.5)}\right], \tag{4.8}$$

$$OSAVI = \frac{(NIR - R)}{(NIR + R + 0.16)}, \tag{4.9}$$

$$GOSAVI = \frac{(NIR - G)}{(NIR + G + 0.16)}, \tag{4.10}$$

$$MSAVI2 = 0.5\left[\,2\,(NIR + 1) - \sqrt{(2NIR + 1)^2 - 8(NIR - R)}\,\right], \tag{4.11}$$

$$EVI = G * \frac{(NIR - R)}{(NIR + C1 * R - C2 * B + L)}, \tag{4.12}$$

where for example L=1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5.

4.4. NDVI Challenges and Complexities in Estimating Yield

There have been a number of challenges when using NDVI to estimate crop yield, and so care must be taken when using NDVI. Some of these challenges have been touched on above, and the above formulas contain attempted improvements regarding NDVI. Most of the main NDVI challenges are summarized below:

1. *Cloud Impacts*: The presence of clouds may reduce NDVI values (thereby indicating lower yield, less vegetation than actually exists). In order to overcome the challenge of clouds, a composite image may be constructed from daily images taken over a period of 10 days, for example. This may allow enough cloud free days to be captured in order to make a suitable image every 10 days. Thick clouds may be easier to detect and adjust for, but thin clouds may be harder to detect, and it may be more difficult to make adjustments or corrections for thin clouds.

2. *Atmospheric Impacts*: The amount of water vapor in the atmosphere and the composition of the atmosphere may impact the NDVI measurements from the satellite. Therefore, NDVI calculations can often be adjusted for water vapor and atmosphere composition.

3. *Soil Impacts*: Soils are darker when wet, and so if soil has more water, it may appear darker, as the soil reflectance is related to soil water content. If for example, spectral response is different for the two bands (NIR and VIS), then NDVI will give a different measurement when there is more soil moisture. In other words, the NDVI can change because of changes in soil moisture (dryer or wetter), rather than because of a change in the yield (plant density).

4. *Spectral Measurement Effects Related to Satellite Sensors*: This arises because a sensor on one satellite maybe be different than on another satellite (e.g. position, width, and shape of the spectral bands), and so measurements may be inconsistent from one satellite to the next. For example, NDVI measurements from a new satellite may not be compatible with measurements from an older satellite with different sensors. As well, as satellites become older, their sensors may potentially degrade, and early measurements may not be completely consistent with older measurements.

5. *Angular Geometry of Illumination*: NDVI may be affected by the angular geometry of illumination regarding the target (e.g. the plant), during the measurement, and this may require correction or making adjustments, and satellites may also drift somewhat over time, affecting the angle.

6. *Saturation Impacts*: As crop yield becomes very high (e.g. plant density becomes very high), then yield may increase more than NDVI. In other words, NDVI may underestimate crop yield at high yield levels. However, this is less of a

problem for lower yield situations, such as pasture, or dryer land areas. Various corrections have been suggested for this, including using EVI, using the simple ratio of NIR/VIS, or using NDWI (Normalized Difference Water Index).

4.5. Biophysical Variables (Parameters) Approach for Estimating Yield

In general, the biophysical variable (parameter) approach is used in order to overcome many of the various challenges faced by NDVI, as mentioned above. Leaf Area Index (LAI) and fAPAR are popular biophysical variables, and these can be used to estimate yield. Biophysical variable approaches are more recent than NDVI vegetation index approaches, and a number of researchers believe them to be superior to NDVI related approaches for estimating yield (Baret & Weiss, 2010; Camacho & Torralba, 2011).

The yield of a crop depends on photosynthesis, photosynthetically active radiation (PAR) absorbed (e.g. sunlight), along with temperature, water, nutrients, and other factors. The amount of absorbed sunlight (PAR) depends on the amount of incoming sunlight and the plants ability to absorb the sunlight. The amount of incoming sunlight can be measured, and the ability of the plant to absorb sunlight can be measured by the plant leaf area, or leaf area index (LAI), which is a biophysical variable that can be used to estimate crop yield.

Related to LAI is fAPAR (also commonly referred to as FPAR), which refers to the fraction of absorbed PAR (APAR), to incoming PAR. fAPAR = APAR/PAR, and is between 0 and 1. This measurement depends mainly on the leaf area of the plant (canopy), and is therefore related to the leaf area index (LAI), (Rembold, Atzberger, Savin, & Rojas, 2013). Some of the main factors influencing PAR, (and fAPAR) in order of importance are: sun zenith angle, soil optical properties, leaf angle distribution, leaf optical properties (e.g. leaf pigment concentration), and leaf area index (Atzberger, 1997).

fCover is a popular biophysical variable, and is often used along in the following group of three fractional measures together: fCover, fBrown, and fSoil. fCover represents the proportion of ground covered by active vegetation when observed vertically. fCover is calculated from the Leaf Area Index (LAI), and other canopy structural characteristics. However, it does not depend on geometry of illumination, and some researchers suggest that biophysical variables such as fCover may perform better than traditional approaches such as NDVI (Baret & Weiss, 2010). As well, others claim that fCover is superior to NDVI because of its robust properties (Camacho & Torralba, 2011).

fBrown is another popular biophysical parameter, along with the other two fractional measures fCover and fSoil. fBrown is the fraction of brown vegetation cover. This is also referred to as the non-photosynthetic vegetation (NPV), and accounts for the brown part of vegetation, just as fCover accounts for the green part of vegetation. Examples of fBrown may include crop residue, dry grassland, tree branches or trunks, and crops in later or end stages of the growing season that have turned color and passed the green stage. Similar to fCover, fBrown does not depend on geometry of illumination.

fSoil is another biophysical variable, and is the fraction of soil that is visible vertically. It can represent bare soil, or holes in canopies. The three fractions together, fCover, fBrown, and fSoil, give a more complete view of the vegetation.

In future, advances in satellite based yield estimation may include more testing of the combining of weather data (temperature, sunlight, precipitation) with NDVI, or biophysical variables, to determine if yield estimation can be improved by including weather data. Also, hyperspectral imaging is a newer form of satellite imaging. It uses many spectrums or bands (Goel et al., 2003), and has become more widely available as satellite technology has improved over time. Hyperspectral imaging is in contrast to the relatively few spectrums or few bands (e.g. VIR, Red (R), Blue (B), Green (G)) used by NDVI and its related measures. Given the additional information that can be gained from hyperspectral imaging, it is likely to become more popular in future, and may enhance accuracy of yield estimation (Mulla, 2013).

SECTION 5

Airbus Defence & Space Grassland Production Indices (GPI's)

Dr. Antoine Roumiguie, Fanny Rosset, Henri Douche

5.1. Technical Specification of the Airbus Defence & Space Overland Grass Production Index Processing Chain

The Grassland Production Index (GPI) processing chain is a fully automatic process. The basic algorithm is shown Figure 5.1. Biophysical parameters are calculated using the Overland image processing software developed by Airbus Defence & Space. This tool extracts vegetation parameters by inverting a radiative transfer model that couples scene and atmospheric models (Poilvé, 2010).

In this study, two GPI are tested. The difference between these indices comes from the biophysical parameter used. The historical processing chain of the GPI is built on the fCover parameter. This is based on the experience in France where GPI is commercialized to private insurers. The other biophysical parameter tested here is the fAPAR.

GPI_1: Overland fCover

GPI_2: Overland fAPAR

In the description of the processing chain, the term "biophysical parameter" refers to fAPAR and fCover. Note also that when fCover is cited in figures or equations, it also implies fAPAR as their implementation in the GPI production is exactly the same.

5.1.1. *Medium Resolution Remote Sensing Data used in the Overland Software Grassland Production Index Processing Chain*

The Overland image processing software developed by Airbus Defence & Space is used to develop a Grassland Production Index. The required inputs for the GPI processing chain are two MODIS Terra products, including calibrated radiances with five bands (between 0.45 and 2.20 μm) L1B at 500 m spatial resolution (data product MOD02HKM), and calibrated radiances with two bands (between 0.62 and 0.88 μm) L1B at 250 m spatial resolution (data product MOD02QKM). Geometric corrections are made to the images using an auxiliary file containing geolocation fields L1A at 1 km spatial resolution (data product MOD03) with the MODIS Reprojection Tool Swath (MRTSwath deployed by the Land Processes Distributed Active Archive Center at the U.S. Geological Survey Earth Resources Observation and Science Center and the South Dakota School of Mines and Technology (2011)).

Biophysical processing of the MR remote sensing data is conducted on the two bands with a spatial resolution of 250 m (bands 1 and 2), and the five bands with a spatial resolution of 500 m (bands 3 to 7).

In the context of an insurance product, it is necessary to have a backup solution in case the MODIS images become unavailable. Different solutions are feasible with the MERIS sensor (to cover the period before 2012), and the MODIS Aqua and now Sentinel-3 (launched in February 2016) sensor. Thanks to the strong correlation between biophysical parameters computed with each of these sensors, GPI is sensor insensitive. To ensure compatibility with MERIS and Sentinel-3 sensors, daily biophysical parameters are produced at 300 m spatial resolution.

5.1.2. *Modelling the Biophysical Processes*

The overall approach is based on physical modelling of the remote sensing signal from the Earth's surface to the satellite sensor. This includes the use of reflectance models to simulate the response from the vegetation canopy, and the use of an atmospheric model to simulate the scene illumination and transfer through the atmosphere. The considered products are biophysical parameters that either are direct inputs to the models (so direct output from the inversion process) or are by-products of the model computations. All of this modelling fully takes into account the sensor/sun directional conditions. The retrieval methodology uses inversion of the coupled scene and atmospheric models in a single step. This means that both the vegetation and atmospheric parameters are retrieved together in the same inversion process. This methodology was initially developed to process images of agricultural areas in order to retrieve biophysical information on crop field plots. The models were then later extended to simulate any type of canopies (not only crop canopies) and so to be applicable to a wide range of landscape conditions. In addition, the vegetation model was upgraded to a canopy model to be applicable to low and medium resolution data (e.g. MODIS/Sentinel-3), for which the assumption of a homogeneous pixel is no longer required. Retrieving all parameters from the same inversion process ensures that the produced set of parameters is fully consistent. The image processing software, Overland, integrates several recently developed models (Jacquemoud et al., 2009) including:

- Low Resolution Transmission (LOWTRAN) (Kneizys et al., 1988) for the atmospheric component.
- Model of leaf optical Properties Spectra (PROSPECT) (Jacquemoud & Baret, 1990) and Scattering by Arbitrarily Inclined Leaves (SAIL) (Verhoef, 1984) for the vegetation component. The vegetation model has been upgraded by adding a brown contribution (for non-productive vegetation) to the foliage. A uniform canopy model would consider a homogeneous mixture of green and brown leaves, characterized by separate PROSPECT variable descriptions.
- Soil reflectance model fully developed by Airbus, which is a needed input to the overall model and is obtained by capturing a spectral signature of local soils from one satellite image. This reflectance is allowed to vary locally both in time and space depending on wetness and roughness of the soil surface.

This step in the GPI processing chain is shown in Figure 5.1 A.

5.1.3. Image Compositing Process

One of the main issues in using Medium Resolution images from an optical sensor for vegetation monitoring is to overcome persistent cloud cover. The best solution is to create synthesis images over a given period in order to select the best available data for each area. During the processing, a compositing algorithm generates seamless 10-day maps of major vegetation parameters, including fCover. For each pixel, fCover in a 10-day period is selected according to the Maximum Value Composite method (Holben, 1986) applied to the spatially filtered fCover information of each observation (Figure 5.1 B).

5.1.4. Disaggregation

One MR pixel may contain different land cover types, therefore, a disaggregation method based on a statistical approach originally applied to reflectances (Di Bella et al., 2004; Faivre & Fischer, 1997) was used to determine fCover/fAPAR values for grassland (Figure 5.1 C). This method estimates fCover/fAPAR values for each land cover class from the input of fCover/fAPAR estimates for a population and an *a priori* knowledge of each land cover classs contribution to each pixel (local aspect). Consequently, fCover/fAPAR is calculated at an Elementary Statistical Unit (ESU) scale. Surfaces of each land cover in the ESU are combined and form the final land cover database.

5.1.5. Definition of the Phenological Parameters

From the analysis of the biophysical parameters time series, it is possible to extract information about the phenology of the grassland cover. For the GPI, the start/end of the growing season are determined for each UAI trough time series analysis. Each steps are detailed here:

- The 10-days data resulting of the disaggregation steps are interpolated (linear interpolation) to create daily time series, as shown in Figure 5.2.
- Then, a time filter (rolling 15-days average) is applied over the daily values of the biophysical parameter, as shown in Figure 5.3.
- These two previous steps are realized for each year available in the historic. From these daily values of the parameter, the historic mean is computed (curve in black bold). Each year are represented in different colours, as shown in Figure 5.4.
- The analysis of the historical curve allows defining average Start/End of season (SOSh and EOSh). These dates are determined when the curve cross the Non-Productive Vegetation (NPV) threshold during an increasing/decreasing phase (Figure 5.5). NPV computation is given according to

$$NPV = min(fCover_i) + 0.2 * (max(fCover_i) - min(fCover_i)) \tag{5.1}$$

- Once SOSh/EOSh have been determined, the same methodology is applied to each annual time series in order to determine SOSa and EOSa. These dates are within a time period of 30 days around SOSh/EOSh. As illustrated in Figure 5.5, it allows considering slightly different periods of the year to observe annual production because growing period may change according weather conditions. This determination of these phenological indicators is fully automatic and driven by the status of the vegetation.

5.1.6. Computation of the GPI

The GPI is derived from the fCover/fAPAR integral and used as a surrogate for Grassland production for a given period of time (Equation 5.2). A fixed factor (13) has been introduced in order to simulate radiation data. It is meaningful as long as agronomic modelling, including weather variables, could be introduced later during this project in the GPI calculation.

$$GPI_n = \sum_{i=SOS}^{EOS} 13 * [fCoverGrassland_i - NPV]^+ \tag{5.2}$$

The GPI is calculated for a year n and is the sum of daily fCover'fAPAR grassland ($fCoverGrassland_i$) from which the part characterizing the proportion of the Non-Productive Vegetation (NPV) is subtracted (Figure 5.1 D). The NPV parameter corresponds to biomass that could not be harvested. Figure 5.7 displays the representation of the annual GPI of one grid.

5.1.7. Computation of the Variation in Biomass Production Ratio

The production shortfall, or excess, corresponds to the ratio between the annual GPI and the historical reference GPI.

$$\Delta GPI_n = \frac{GPI_n}{historical.reference(GPI_n)} \tag{5.3}$$

In Equation 5.3, the historical reference GPI can be calculated in many different ways. For example, a simple average or olympic average over a defined number of years, and step is shown within the processing chain in Figure 5.1 E. The choice of the calculation method for reference GPI has to be made carefully, and must consider both local laws and regulation, as well as the design of the insurance policy. Also, it is important to note that the calculation of the reference GPI will impact the sensitivity of the insurance policy.

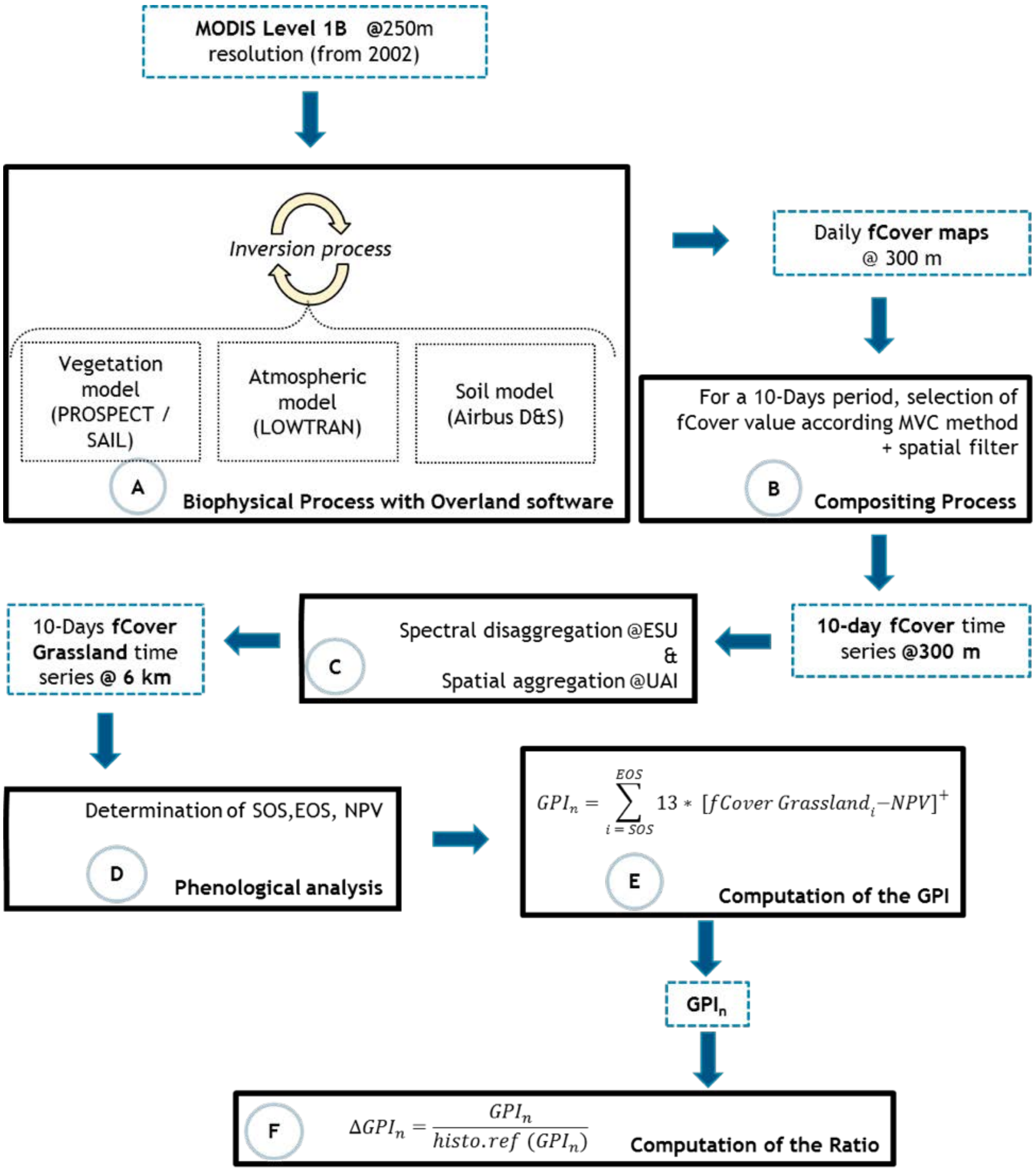

Figure 5.1: The processing chain of the Grassland Production Index (GPI). Rectangles in black bold illustrate the main step of the processing chain. Green dotted rectangles are the intermediate products where PROSPECT = Properties Spectra, SAILn = Scattering by Arbitrarily Inclined Leaves, LOWTRAN = Low Resolution Transmission, Airbus D & S = Airbus Defence & Space, MVC = Maximum Value Composite, NPV = Non-Productive Vegetation, and fCover = Fraction of Green Cover. This figure has been reproduced from an original publication by Roumiguié, Jacquin, Sigel, Poilvé, Hagolle, and Daydé (2015), licensed under the Creative Commons Attribution 4.0 International License (`http://creativecommons.org/licenses/by/4.0/`).

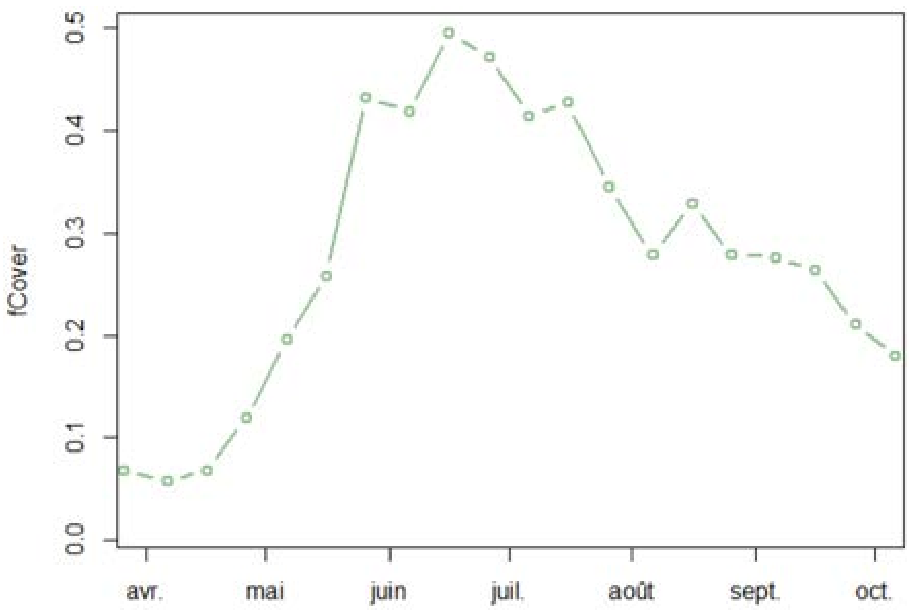

Figure 5.2: 10-days fCover values interpolated to create daily time series

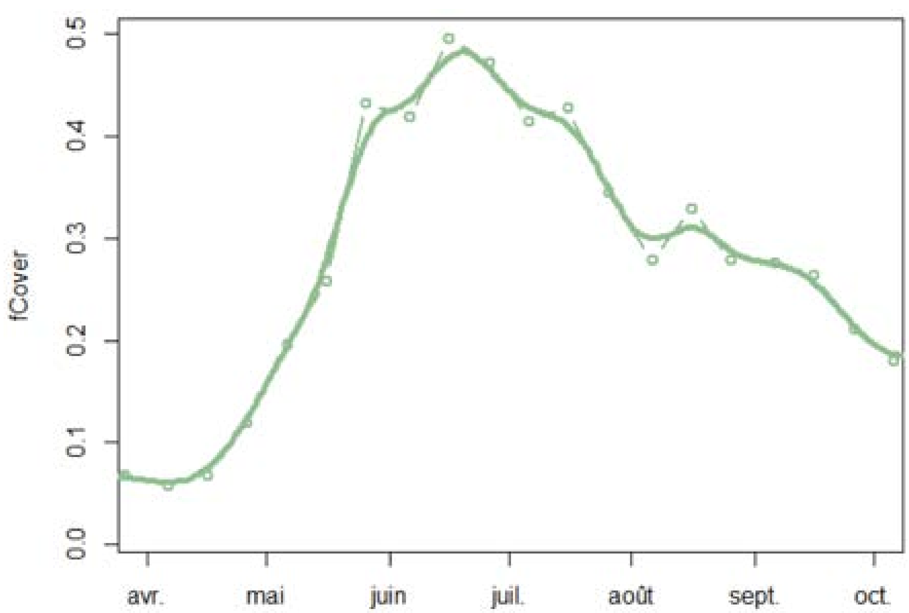

Figure 5.3: Rolling 15-days average on the daily data interpolated

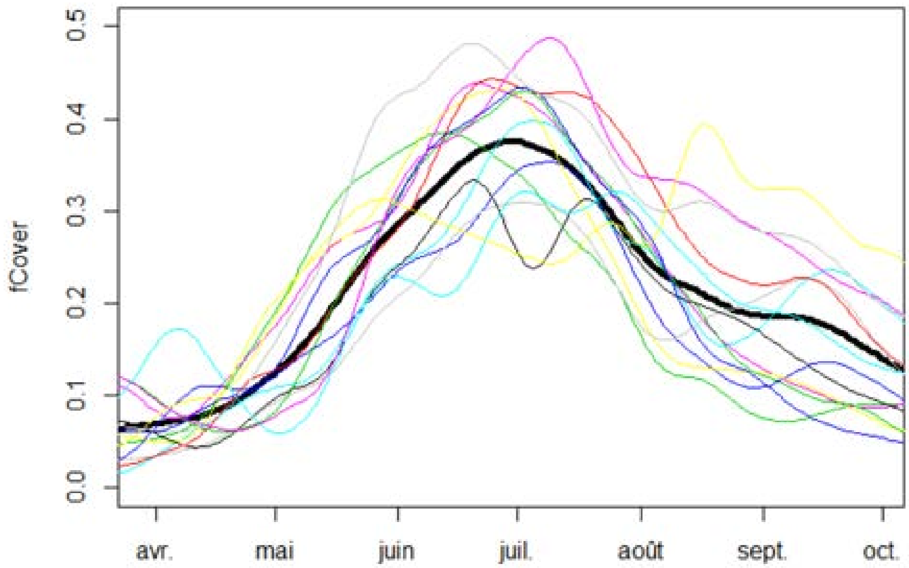

Figure 5.4: Representation of all years time series and average (curve in black bold)

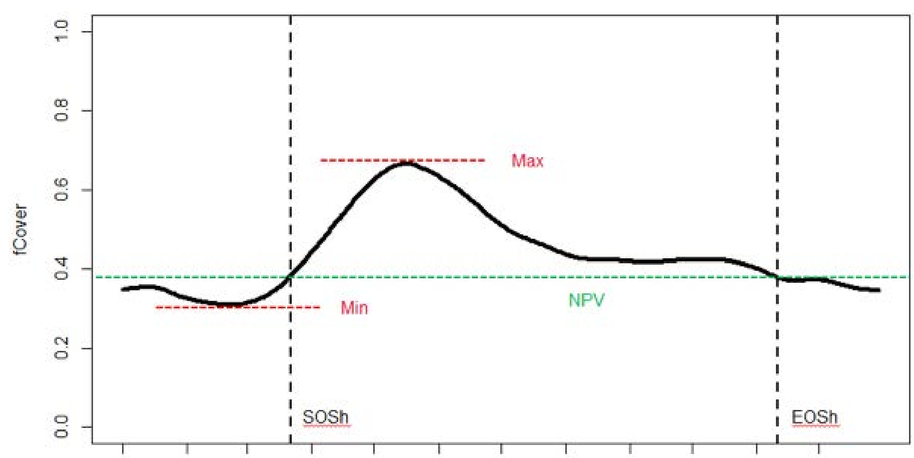

Figure 5.5: Methodology to determine phenological parameters on the historic curve)

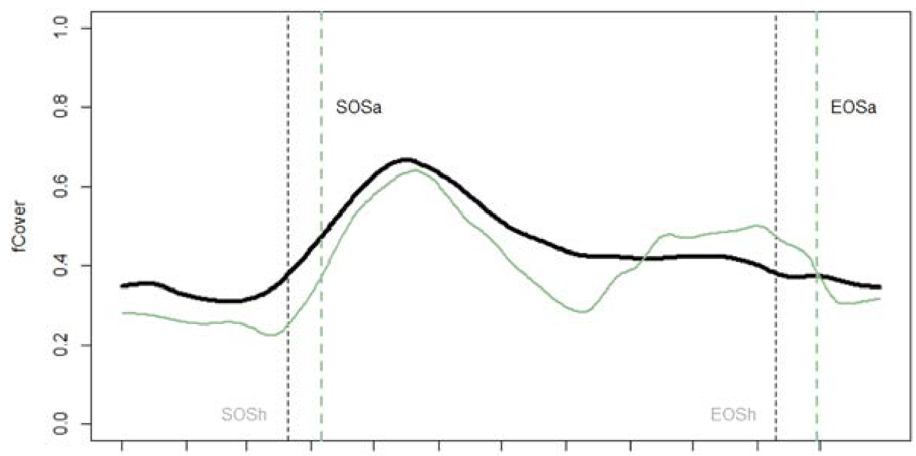

Figure 5.6: Methodology to determine annual phenological parameters)

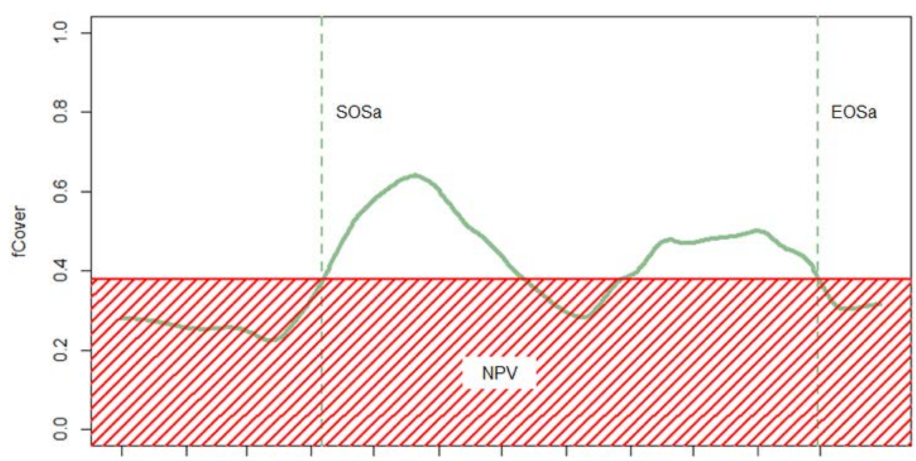

Figure 5.7: Representation of the annual GPI of one grid.)

SECTION 6

Alternative Forage Production Indices (FPI's)

Dr. Brock Porth, Dr. Lysa Porth, Dr. Milton Boyd, Dr. Ken Seng Tan

In this section, sixteen alternative Forage Production Indices (FPI's) are presented, which are compared to the ground-truth forage yield data. The FPI's include those based on vegetation indices, biophysical parameter indices, as well as weather station indices. In this section, a brief overview of each of the indices is provided.

6.1. Vegetation Indices

Eleven vegetation indices are considered in this project, which are based on several methods described in literature and computed from publicly available data.

6.1.1. Normalized Difference Vegetation Index (NDVI)

The first three FPI's are the Normalized Difference Vegetation Index (NDVI). The first NDVI calculation, FPI_1: NDVI AVHRR 1 km, uses satellite data at the 1 km resolution from the Advanced Very High Resolution Radiometer (AVHRR) of the National Oceanic and Atmospheric Administration (NOAA) series of Earth observation (EO) satellites, and is obtained from Statistics Canada. The current pasture insurance program in Alberta uses this 1km AVHRR-NDVI, therefore, this FPi serves as an important comparison.

The second NDVI calculation, FPI_2: NDVI MODIS 500 m - Daily Observations, uses 500 m resolution satellite imagery data obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS), onboard the multi-national Terra scientific research satellite operated by the National Aeronautics and Space Administration (NASA). The MODIS Reflectance MCD43A4 product provides 500-meter reflectance data adjusted using a bidirectional reflectance distribution function (BRDF) to model the values as if they were taken from nadir view. The MCD43A4 product is a level-3 gridded data set in Sinusoidal projection and is provided daily.

The third NDVI calculation, FPI_3: NDVI MODIS 250 m - 8 Day Observations, uses 250 m resolution satellite imagery data is obtained from MODIS, onboard NASA. The data are distributed as *data products* through the Level-1 and Atmosphere Archive & Distribution System (LAADS) Distributed Active Archive Center (DAAC), part of the Terrestrial Information Systems Laboratory at NASA Goddard Space Flight Center in Greenbelt, MD, United States (NASA, 2017b). For the NDVI calculation, the MOD09GQ Version 6 data product provides the input surface reflectance data for the near-infrared, and red bands of the electromagnetic spectrum, and is provided every 8 days.

6.1.2. Green Normalized Difference Vegetation Index (GNDVI)

The next two FPI's are the Green Normalized Difference Vegetation Index (GNDVI). The fourth FPI, FPI_4: GNDVI MODIS 500 m - Daily Observations, uses 500 m resolution satellite imagery obtained from MODIS, onboard NASA. This FPI uses the MCD43A4 product to provide 500-meter reflectance data adjusted using a bidirectional reflectance distribution function (BRDF) to model the green and near-infrared bands of the electromagnetic spectrum, and is provided each day.

The fifth FPI, FPI_5: GNDVI MODIS 250 m - 8 Day Observations, uses 250 m resolution satellite imagery data obtained from MODIS, onboard NASA. This FPI uses the MODo9GQ product to provide input surface reflectance data for the green and near-infrared bands, and is provided every 8 days.

6.1.3. Enhanced Vegetation Index (EVI)

The sixth and seventh FPI's are based on the Enhanced Vegetation Index (EVI). FPI_6: EVI MODIS 500 m - Daily Observations, uses the MCD43A4 product to provide 500-meter reflectance data adjusted using a bidirectional reflectance distribution function (BRDF) to model the blue, near-infrared, and red bands of the electromagnetic spectrum, and is provided each day.

The seventh FPI, FPI_7: EVI MODIS 250 m - 8 Day Observations, uses 250 m resolution satellite imagery data obtained from MODIS, onboard NASA. This FPI uses the MODo9GQ product to provide input surface reflectance data for the blue, near-infrared, and red bands, and is provided every 8 days.

6.1.4. Modified Soil Adjusted Vegetation Index (MSAVI2)

The next two FPI's are based on the Modified Soil Adjusted Vegetation Index (MSAVI2). FPI_8: MSAVI2 MODIS 500 m - Daily Observations, uses the MCD43A4 product to provide 500-meter reflectance data adjusted using a bidirectional reflectance distribution function (BRDF) to model the near-infrared and red bands, and adjusts for the influence of the soil background, and is provided each day.

The ninth FPI, FPI_9: MSAVI2 MODIS 250 m - 8 Day Observations, uses 250 m resolution satellite imagery data obtained from MODIS, onboard NASA. This FPI uses the MODo9GQ product to provide input surface reflectance data for the near-infrared and red bands, and adjusts for the influence of the soil background, and is provided every 8 days.

6.1.5. Optimized Soil Adjusted Vegetation Index (OSAVI)

The next two FPI's are based on the Optimized Soil Adjusted Vegetation Index (OSAVI). FPI_{10}: OSAVI MODIS 500 m - Daily Observations, uses the MCD43A4 product to provide 500-meter reflectance data adjusted using a bidirectional reflectance distribution function (BRDF) to model the near-infrared and red bands, and is optimized for agricultural modelling and adjusts for the influence of the soil background. This product is provided each day.

The eleventh FPI, FPI_{11}: OSAVI MODIS 250 m - 8 Day Observations, uses 250 m resolution satellite imagery data obtained from MODIS, onboard NASA. This FPI uses the MODO9GQ product to provide input surface reflectance data for the near-infrared and red bands, and is optimized for agricultural modelling and adjusts for the influence of the soil background. This product is provided every 8 days.

6.2. Biophysical Parameter Indices

Two FPI's based on biophysical parameters are constructed, which are based on methods described in literature and computed from publicly available data.

6.2.1. Leaf Area Index (LAI)

The first FPI based on biophysical parameters is FPI_{12}: LAI MODIS 500 m - Daily Observations. This FPI uses the MOD15A2H version 6 MODIS Level 4 product to provide Leaf Area Index (LAI) for an 8-day composite data set with 500-meter pixel size. LAI is defined as the one-sided green leaf area per unit ground area in broadleaf canopies and is one-half the total needle surface area per unit ground area in coniferous canopies.

6.2.2. Fraction of Incident Photosynthetically Active Radiation (FPAR)

The second FPI based on biophysical parameters is FPI_{13}: FPAR MODIS 500 m - Daily Observations. This FPI uses the MOD15A2H version 6 MODIS Level 4 product to provide Fraction of Incident Photosynthetically Active Radiation (FPAR) for an 8-day composite data set with 500-meter pixel size. FPAR is defined as the fraction of incident photosynthetically active radiation (400-700nm) absorbed by the green elements of a vegetation canopy.

6.3. Weather Station Indices

The third grouping of FPI's are based on data obtained from ground weather stations, and three indices are considered.

6.3.1. Accumulated Precipitation (AccPcpn) Weather Station

The first FPI based on weather station data is FPI_{14}: Accumulated Precipitation Weather Station. Daily precipitation data is summed to create an index of accumulated values, which are matched to the ground truth forage yield data based on selecting the weather station geographically closest to the location of the test site.

6.3.2. Heating Degree Days (HDD) Weather Station

The second FPI based on weather station data is FPI_{15}: Heat Degree Days Weather Station. Daily temperature data is used to construct a Heating Degree Days (HDD) index. The index considers when the daily mean temperature falls below 65 °F. The daily mean temperature is found by adding together the high and low temperature for the day and dividing by two. When the mean temperature is above 65 °F, the HDD total is zero. If the mean temperature is below 65 °F, the HDD amount is the difference between 65 °F and the mean temperature.

6.3.3. Cooling Degree Days (CDD) Weather Station

The third FPI based on weather station data is FPI_{16}: Cooling Degree Days Weather Station. The CDD index is related to the HDD index previously described, where the daily temperature data is used to construct a Cooling Degree Days (CDD) index. The index considers when the number of degrees that a day's average temperature is above 65 °, which is the temperature above which buildings need to be cooled.

SECTION 7

University of Manitoba Analysis and Interpretation of Results

Dr. Brock Porth, Dr. Lysa Porth, Dr. Milton Boyd, Dr. Ken Seng Tan, Dr. Wenjun Zhu

7.1. Background

This section is prepared by the University of Manitoba research team, and provides an independent analysis of the performance of the various indices constructed for predicting forage yield. In the appendix, additional analysis performed by the SCOR research team is provided. This section is organized as follows. First, an overview of the statistical validation methods regarding the assessment of the indices is provided. Next, background information relevant to the overall analysis is summarized. Following this, analysis of the two Grass Production Indices (GPI's) computed by Airbus Defence & Space using their Overland software is presented. Analysis of nine alternative Forage Production indices (FPI's) is then presented. In each subsection, a discussion on limitations relevant to this phase of the research is included.

7.1.1. Statistical Validation

The focus of this section is on statistical validation methods regarding the performance of the Airbus Grassland Production Indices (GPI's) and the alternative Forage Production Indices (FPI's). To validate the indices, three main types of validation are considered, including 1) direct, 2) indirect and 3) the final insurance policy validation. The first type of validation is a direct measure between the constructed indices and the ground truth forage yield data. The second type of validation is an indirect measure between the Medium Resolution (MR) and High Resolution (HR) imagery data, which is done only for the Airbus GPI's and not the alternative FPI's. The third type of validation focuses on the final insurance policy in order to understand how the insurance indemnity calculated by the underlying index (GPI or FPI) compares to the actual loss experienced on the farm. Each of these three types of validation are discussed below in further detail.

7.1.1.1. Validation of the Index and Ground Truth Forage Yield Data

To verify that the underlying index is a good representation of the loss experienced on the farm, this validation step quantitatively assesses the relationship between the estimated forage yield computed via the Airbus GPI's or alternative FPI's and the ground truth forage yield data at the individual farm level.

It is of interest to understand how the various indices perform under different scenarios, including geo-spatial (meaning across different geographic regions, soil zones, etc.), intra-temporal (meaning variation within the growing season attributed to different critical growth phases of the forage crop) and inter-temporal (meaning across multiple years attributed to various extreme weather events, which could include excess moisture, drought, etc.). Given that the GPI or FPI is intended to be used in an index-based insurance policy, special attention is given to the relationship between the index and low yields (Kapphan, 2011; Leblois & Quirion, 2013). This is because low yields correspond to scenarios where producers should receive an indemnity payment to cover their forage production shortfall.

Correlation analysis is one of the most commonly used methods to understand how accurate the index can predict the yield relative to the ground-truth measured yield, and this is done by calculating the correlation coefficient between the two (Berg, Quirion, & Sultan, 2009; Leblois & Quirion, 2013; Makaudze & Miranda, 2010; Wehlage, Gamon, Thayer, & Hildebrand, 2016). Another statistical approach commonly used in validating vegetation indices is regression analysis (Atzberger, Guérif, Baret, & Werner, 2010; Huang, Wang, Li, Tian, & Pan, 2013; Labus, Nielsen, Lawrence, Engel, & Long, 2002; Manjunath, Potdar, & Purohit, 2002; Potdar, Manjunath, & Purohit, 1999; Quarmby, Milnes, Hindle, & Silleos, 1993; Rasmussen, 1998; Rojas, 2007; Turvey & Mclaurin, 2012; Wall, Larocque, & Léger, 2008; Wehlage et al., 2016), which involves identifying the relationship between a dependent variable (e.g. ground truth forage yield data) and one (or more) independent variable(s) (e.g., the various GPI's or FPI's). A model of the relationship is hypothesized, and estimates of the parameter values are used to develop an estimated regression equation. The least square regression method is one of the most commonly use methods. In general, the following procedure can be followed to perform the regression analysis.

Step A: Develop a model describing the relationship between the ground truth forage yield data and the index. If we denote the yield time series in year as y_t, and the monthly index (i.e. Airbus GPI's or alternative FPI's) in month of year as $index_{m,t}$, then the regression model in general can be expressed as

$$y_t = f(index_{m,t}) + \epsilon_t \tag{7.1}$$

where $f(index_{m,t})$ is the functional form of the regression model, and ϵ_t refers to the residuals of the model.

Step B: Calculate the root mean square error (RMSE) of the model. The RMSE values can be calculated according to

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}. \tag{7.2}$$

Large R^2 or small $RMSE$ values indicate a better GPI/FPI insurance design.

Correlation and regression analyses are related in the sense that both assess the relationships among variables. In general, as described in section 4, in dry years the linear model may overestimate yield because high biomass may not always be an indication of high yield. Similarly, in wet years the linear model may underestimate yields because the index can become saturated and not estimate a sufficiently high yield. Therefore, a more complex nonlinear relationship may need to be investigated.

Several studies have used the linear regression model to describe the relationship between NDVI and wheat yield in different regions. For example Lopresti, Di Bella, and Degioanni (2015) study the relationship between NDVI and wheat yield using a linear regression model, where the dependent variable is represented by wheat yield and the independent variable by NDVI.

Aparicio, Villegas, Casadesus, Araus, and Royo (2000) used Pearson correlation coefficients to study the relationship between radiometric indices and biological variables. The percentage of grain yield variation explained by the progressive addition of each spectral reflectance index measured at different growth stages was assessed by means of the coefficient of determination of a multilinear fitting. Hansen and Schjoerring (2003) compare reflectance measurement of canopy biomass and nitrogen status in wheat crops using NDVI and partial least squares regression. Validation of the models was performed using regression analysis and root mean square error (RMSE). Regression analysis provides information on the relationship between the observed and predicted variables to the extent that information is contained in the data. They also plot the observed data against predicted values. Correlation analysis between the actual and predicted values was also calculated to assess the goodness of fit. The coefficient of determination R^2 was used as a relative index of model performance, and RMSE was used to compare the observed and predicted crop coefficients. This provided an indication of both bias and variance.

Further examples of the use of the linear regression model as a validation method are found in Kamble, Kilic, and Hubbard (2013), where NDVI data from MODIS is compared to a crop coefficient. Similarly, Wehlage et al. (2016) study crop yield forecasting in the Canadian Prairies using NDVI data from the MODIS sensor. Regression analysis is used with power function models to explain the crop yield variability in barley, canola, field peas, and spring wheat, and their findings are reported using RMSE values. Further, Roumiguié, Jacquin, Sigel, Poilvé, Hagolle, and Daydé (2015) validate a forage index based on fCover derived from MODIS time series data. They use an upscaled approach based on direct validation which compares GPI with field-collected biomass data and high spatial resolution (HR) time series images. They perform validation of their models by comparing differences in R^2 and RMSE.

7.1.1.2. Indirect Validation of MR and HR Satellite Imagery

Indirect validation consists of assessing the performance of the Airbus GPI computed from the MR (300 m) and HR (6 to 30 m) time series data as outlined in Roumiguié, Jacquin, Sigel, Poilvé, Hagolle, and Daydé (2015). This validation step offers several advantages over the direct method. First, the use of HR images as the reference allows all forage farms to be considered with an elementary statistical unit (see Section 5.1.4), thereby increasing representativeness. Second, this approach overcomes the temporal sampling issues previously discussed using test site data that is typically collected only once or twice per growing season, given that the HR data can be obtained as frequently as every 2 to 3 days, cloud cover permitting.

Using HR images as an intermediate scale of measurement improves spatial coverage, but, requires an upscaling step that introduces new challenges related to sampling strategy and the processing of HR time series with irregular image acquisition frequencies (Roumiguié, Jacquin, Sigel, Poilvé, Hagolle, & Daydé, 2015). When performing the indirect validation between MR and HR imagery, careful consideration must be given to the quantifying disaggregation effects.

7.1.1.3. Validation of the Insurance Indemnity and Actual Farm Loss

In developing a new insurance policy that is index-based, it is important to consider the basis risk that the producer may be exposed to. Basis risk refers to the mismatch between the indemnity determined by the index and the actual loss on the farm. Much literature has pointed to the challenge of basis risk as a major factor in the successful commercial implementation of index insurance (Miranda & Glauber, 1997). This can include situations when farmers receive an indemnity payment despite having no loss (Type I Error), or alternatively when farmers do not receive an indemnity payment despite experiencing yield shortfall (Type II Error). This validation will be the focus of the next phase of the research.

7.1.2. Review of Data in Alberta and Saskatchewan

In this subsection, the data used to construct the various Airbus GPI's and alternative FPI's are reviewed, along with an overview of the ground truth forage yield data used for validation. Section 3 provides detailed descriptions of the data.

7.1.2.1. Data Used to Construct the Indices

Three different GPI's are produced by Airbus Defence & Space using their proprietary Overland software across the sites in Alberta and Saskatchewan. These three GPI's are based on a biophysical parameter approach, and include 1) fCover, 2) fAPAR and 3) a Smart Grid. Each of the three Airbus GPI's are defined in Section 5 of the report. In addition, nine alternative FPI's are computed from public open-source data across the same test sites in Alberta and Saskatchewan. These nine FPI's are based on three approaches, including vegetation indices, biophysical parameter indices, and weather station indices.

7.1.2.2. Ground Truth Data Used to Validate the Indices

For the province of Alberta, pasture is the focus of the analysis, including for both improved and native. This first phase of the research in Alberta is limited to only pasture data, while the next phase of the research would expand this to include representative hay data as well. For the province of Saskatchewan, hay is the focus of the analysis, including for alfalfa, grass and alfalfa/grass mix. This first phase of the research in Saskatchewan is limited to only hay data, while the next phase of the research would expand this to include representative pasture data as well.

As mentioned in Section 3, there are several potential limitations of the data, including uncertainty surrounding the dates of the yield measurements, the limited frequency of measurements, representativeness of the location of measurements, etc. To help address these potential limitations, the next phase of the research will consider crop-cutting experiments to help ensure that the measured yield used for validating the various indices is representative of actual production.

7.1.2.3. Caution in Interpreting the Results

Before proceeding, it is very important to note the results in this section should be interpreted with caution given that this first phase of the research is preliminary and focuses on an assessment of the feasibility of the satellite-derived indices, rather than the full development and validation of the indices and design of the insurance product, which is the focus of the next phase of the research. The results in this section should also be interpreted with caution given there may be some concern regarding the availability and quality of the ground truth validation data.

Further, it should be noted that the results in this study, such as the correlations, for example, should not be compared to the results reported in other studies. This is because there may be many differences pertaining to the underlying assumptions of the data processing and analysis, and perhaps most importantly differences in the spatial aggregation level of the ground truth yield data used for validation. In general, the higher the spatial aggregation level of the ground-truth yield data the higher the expected correlation with the index. For example, many studies typically consider ground truth yield data spatially aggregated to the township level. Whereas in this study we are considering data that has relatively low spatial aggregation. In Alberta the data is taken at very small areas corresponding to a 1 m by 0.5 m clip frame area. In Saskatchewan the data corresponds to the legal land description (LLD) level, which corresponds to a quarter-section (i.e. 160 acres), or in cases where one producer has more than one quarter section, the yield is averaged across all of the LLD's. However, due to the filtering of the Saskatchewan data described in Section 3, the test sites considered in this analysis are typically restricted to a relatively smaller area of approximately 2 LLD's on average.

In the next phase of the research, it is planned that additional ground truth data will be collected that is representative of the farm-level experience. This will be important in better understanding the basis risk of the insurance product, which indicates the mismatch between the indemnity calculated by the insurance index relative to the actual loss experienced on the farm.

7.2. Review of Spatial Scale of the Indices

The satellite-derived Airbus GPI's and alternative FPI's have various spatial scales. For example, the biophysical parameter calculations are based on a resampled resolution of 300m, and the alternative FPI's are based on resolutions ranging from 250m to 1km. The Airbus GPI's are produced for a square 6km by 6km grid, and this spatial scale of the grid was chosen by Airbus to reflect the current size of the grid used in the operational pasture insurance program in France. In France, the spatial scale of the index is regulated and must be a minimum of 6km by 6km. In Canada, alternative grid sizes will be considered in the next phase of the research. For the alternative FPI's the grid sizes correspond to the satellite pixel resolution (i.e. 250m, 500m, etc). We refer ti the grid size for insurance purposes as the "unit area insurance." A higher resolution, or smaller unit area of insurance has the benefit of providing an insurance program with an underlying index that is more individualized to a producer, rather than covering a larger area. However, potential issues regarding moral hazard must be considered. Moral hazard refers to the situation where the producer has the ability to influence the payout from the index. Therefore, in theory the insurance index could cover a relatively small area, such as a field or an individual producer, or it could cover a relatively larger area, such as a municipality, as examples. Future research regarding the unit area insurance is needed. Figure 7.1 shows a map of spatial scales for the Airbus 6km by 6km grid, the MODIS pixel, and the LLD or quarter section level. The large square in the centre of the image with a thin black border represents the Airbus GPI grid (i.e. 6km by 6km). Within this Airbus square grid there are two smaller shaded green squares that are touching, and these represent two bordering LLD's. Each square represents one LLD that is equivalent to 160 acres. Also within the Airbus GPI grid, there are several 250m MODIS pixels (parallelogram tiles). Approximately 55 LLD's are contained within the Airbus grid.

7.3. Analysis of the Airbus Defence and Space GPI's

In this subsection, three Grassland Production Indices (GPI's) developed by Airbus Defence & Space are analyzed.

7.3.1. Overview

7.3.1.1. Review of Airbus GPI's

Two GPI's were provided by Airbus were described in Section 5, and below they are briefly summarized.

GPI_1: Overland fCover

GPI_2: Overland fAPAR

7.3.1.2. Summary of Validation Protocol

To validate the performance and accuracy of the GPI's, three main types of analysis are considered.

The first analysis considers the GPI generated from the high resolution (HR) satellite data and compares it to the ground truth forage yield data. This exercise is completed using data from the most current crop year, which is 2016, for the fCover and fAPAR GPI's only.

The second analysis compares the GPI's generated from the medium resolution (MR) satellite data with the ground truth forage yield data. This is a very important part of the validation given that operationally it is expected that the MR satellite data would be used to produce the GPI. This step is completed using a detailed time-series of MR images from 2002 to 2016, for all three GPI's.

Figure 7.1: Map of spatial scales for the Airbus 6km by 6km grid, MODIS pixel, and the LLD or quarter section level. The large square in the centre of the image with a thin black border represents the Airbus GPI grid (i.e. 6km by 6km). Within this Airbus square grid there are two smaller shaded green squares that are touching, and these represent two bordering LLD's. Each square represents one LLD that is equivalent to 160 acres. Also within the Airbus GPI grid, there are several 250m MODIS pixels (parallelogram tiles). Approximately 55 LLD's are contained within the Airbus grid.

The third analysis compares the GPI's produced from the MR data and compared to the HR data. The purpose of this step is to compare the output of the two spatial resolutions. This step is completed for the most current crop year, which is 2016, for the fCover and fAPAR GPI's only.

7.3.1.3. Measurement Periods

The ground truth forage yield data in the provinces of Alberta and Saskatchewan are discussed in detail in Section 3.3.2.1. For the province of Alberta the ground truth data is measured twice per year at the clip sites, which includes the months of June and August. However, in the data set it is not known precisely when in these months the yield measurement is taken. A simple correlation analysis was conducted between the index values and ground data using different measurement periods (i.e. from season start to June 1, from season start to June 15, and from season start to June 30 for the first clip and from season start to August 1, from season start to August 15, and from season start to August 30 for the second clip). The highest overall correlations were found to be from season start to June 30 and from season start to August 30, therefore, we use this as the basis for the measurement period considered here for the province of Alberta. However, it should be noted that the time of the measurement likely changes from one year to the next, and this may introduce error into the subsequent analysis. In the next phase of the research the measurement periods will be considered in the collection of new ground truth data. Therefore, for the purpose of this analysis the first period considered is from season start to June 30, while the second period is from season start to August 15. A third way of viewing the results is to consider all of the observations for the months of June and August together (however, it is important to note that this does not mean summing the observations in June and August).

Figure 7.2 shows an example of the daily time series of fCover on which the Airbus GPI_1 is based on the left, and the evolution of the GPI_1 from the start of season to the end of season on the right. The figure shows the values for each year between 2002 and 2016 (the various coloured lines), as well as the average over the entire time period (bold black line) for a sample location in Alberta. In each panel of the figure, the dashed vertical lines indicate the dates June 30 and August 15. From the left panel, it is observed that the cut-off date at which the index is calculated is extremely important - on average GPI_1 increases from roughly 290 at the end of June to 1160 in the middle of August. Even within a single month itself there is large growth - the average GPI_1 increases from 840 to 1160 to 1270 from the beginning, through the middle, up to the end of August, respectively. Also, it is observed that in most years, the GPI still increases after the end of August. Also, for this sample location in both 2015 and 2016 the production years were exceptionally good, and the average is strongly affected by this. Although the figure shows just one location, similar behaviour can be observed for the index in general. For a further description and analysis of the fCover and GPI at various geographic aggregation levels see the SCOR analysis section found in the appendix.

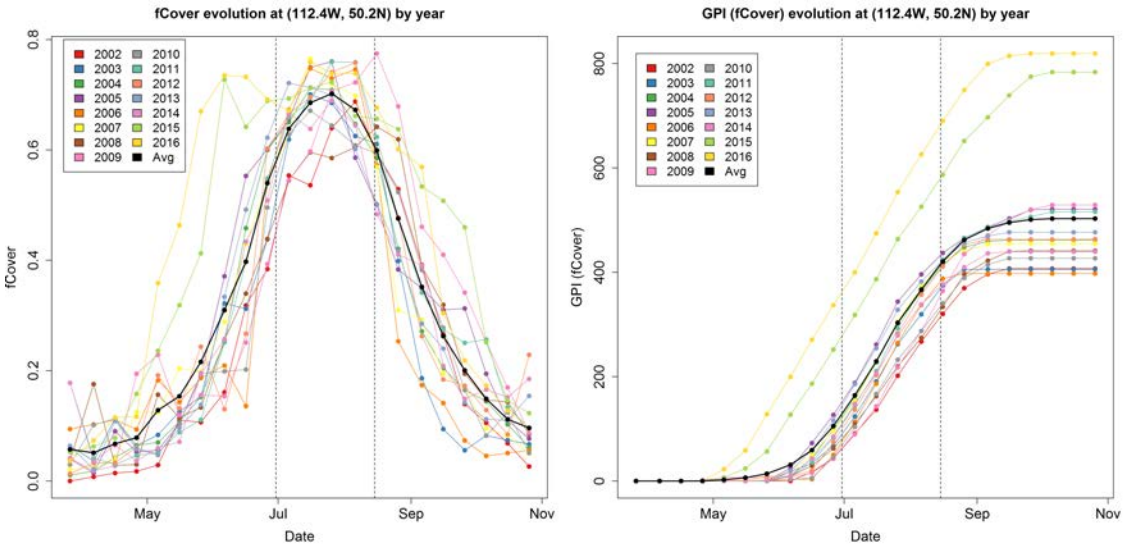

Figure 7.2: Daily Time Series of the Airbus fCover on which the Airbus GPI_1 is based on the left, and the evolution of the GPI_1 from the start of the season to the end of the season on the right

For Saskatchewan, the ground truth data corresponds to data collected for the current tame-hay insurance program, which is described in Section 3. Given that the data corresponds to the insurance program, losses are either measured or yields are reported only at harvest. It is not known the exact date that this yield is measured. Further, there is likely variability from one year to the next making it difficult to align the measurement period of the index relative to the measured ground yield. Therefore, for the purposes of this analysis it is assumed that the period goes from season start to season end, as determined by Airbus.

The second phase of the research will investigate the measurement periods in more detail, as it is expected this will be an important consideration when designing the insurance contract to make it relevant to the producer and limit basis risk.

7.3.2. Analysis of the Airbus GPI's by Grid Cell

In this first subsection of the analysis, the Airbus GPI's are examined over each grid cell (6 km by 6 km area) to better understand the behaviour by region and over time. It should be noted that the index values are estimates of biomass rather than actual yield measurements. The GPI's are produced for the category of Pasture in Alberta and do not distinguish between improved and native pasture at this stage in the research. In Saskatchewan, the GPI's are produced for three categories of tame-hay, including Alfalfa, Grass and Alfalfa/Grass mix.

7.3.2.1. Spatial Observations

For each of the GPI's produced by Airbus, an index value is provided for every 6 km by 6 km grid cell across the provinces of Alberta and Saskatchewan. To get a better understanding of the overall spatial patterns of forage across the two provinces, the average Airbus fCover GPI and fAPAR GPI over the entire sample period from 2002 to 2016 is examined in Figure 7.3 and Figure 7.4, respectively. On average, the results for both the fCover and FAPAR GPI's appear to be quite similar, with lower yields in the middle of the provinces.

To gain further insight regarding the spatial behaviour of the Airbus GPI's, the coefficient of variation (CV) per pixel (the Gaussian CV, which is defined as the ratio of the standard deviation to the mean) is calculated and depicted in Figure 7.5 and Figure 7.6, respectively. The map shows the wide range in forage productivity across the various regions on average over this period. The map shows that areas in the central east and southeast parts of Alberta, as well as the central west and southwest parts of Saskatchewan are the most volatile. Overall, the maps of the CV of the fCover and fAPAR GPI's also appear very similar. The middle of the provinces appear to have the most volatility in yields, while the west part of Alberta and the east part of Saskatchewan seem to be more stable with lower volatility in yields.

7.3.2.2. Temporal Observations

In addition to observing spatial differences of the GPI's across the provinces, it is also interesting to examine spatio-temporal maps of the Airbus GPI's. Figure 7.7 shows maps of the Airbus fCover GPI, and Figure 7.8 for the fAPAR GPI, for each of the years in the sample period from 2002 to 2016. The maps show that 2002, 2003, and 2009 were relatively low production years. The maps corresponding to 2010 and 2016 show relatively higher production years. It is important that the GPI is able to capture differences in yield estimates from year to year. It can also be observed that the range in GPI values can be quite large. For example, in 2016 the average GPI value is approximately 500, while the lowest is 300 and the highest is 900.

In addition to examining the mean GPI values across the years, it is also insightful to calculate the deviation from the mean. Figure 7.9 shows the departure of the value of the Airbus fCover GPI, and Figure 7.10 shows the departure of the value of the Airbus fAPAR GPI, for a given year GPI_i^j from the mean value of all GPI observations GPI_i^{mean} as determined for the years $j = 2002, 2003, ..., 2016$ at a given grid cell location i. The *index* in the figure is calculated as the ratio of the annual GPI difference over the mean GPI value, as described by the following formula:

$$index_i^j = \frac{GPI_i^j - GPI_i^{mean}}{GPI_i^{mean}}. \tag{7.3}$$

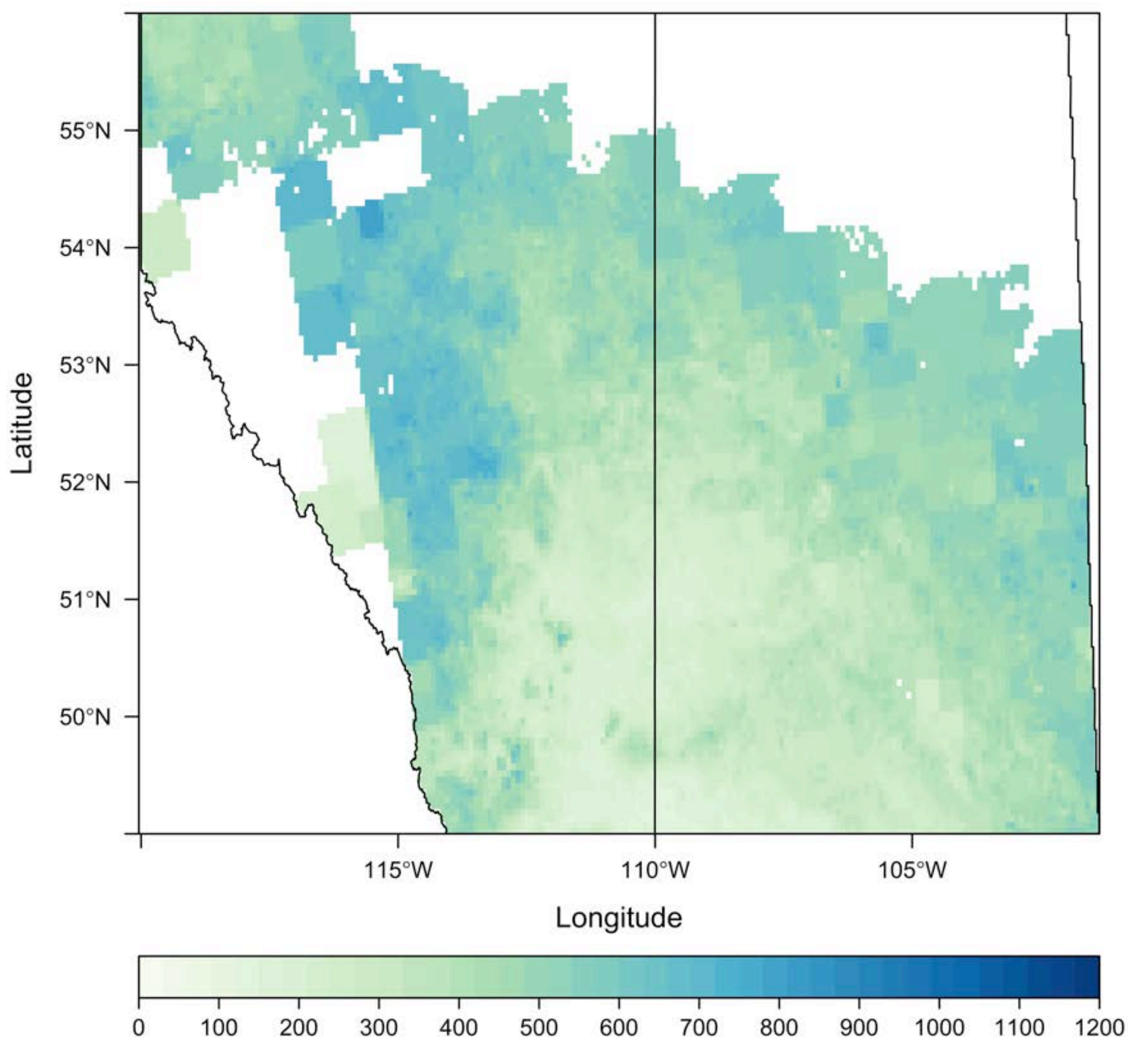

Figure 7.3: Average Values for the Airbus fCover Grass Production Index (GPI) for the Years 2002 - 2016 for Alberta and Saskatchewan.

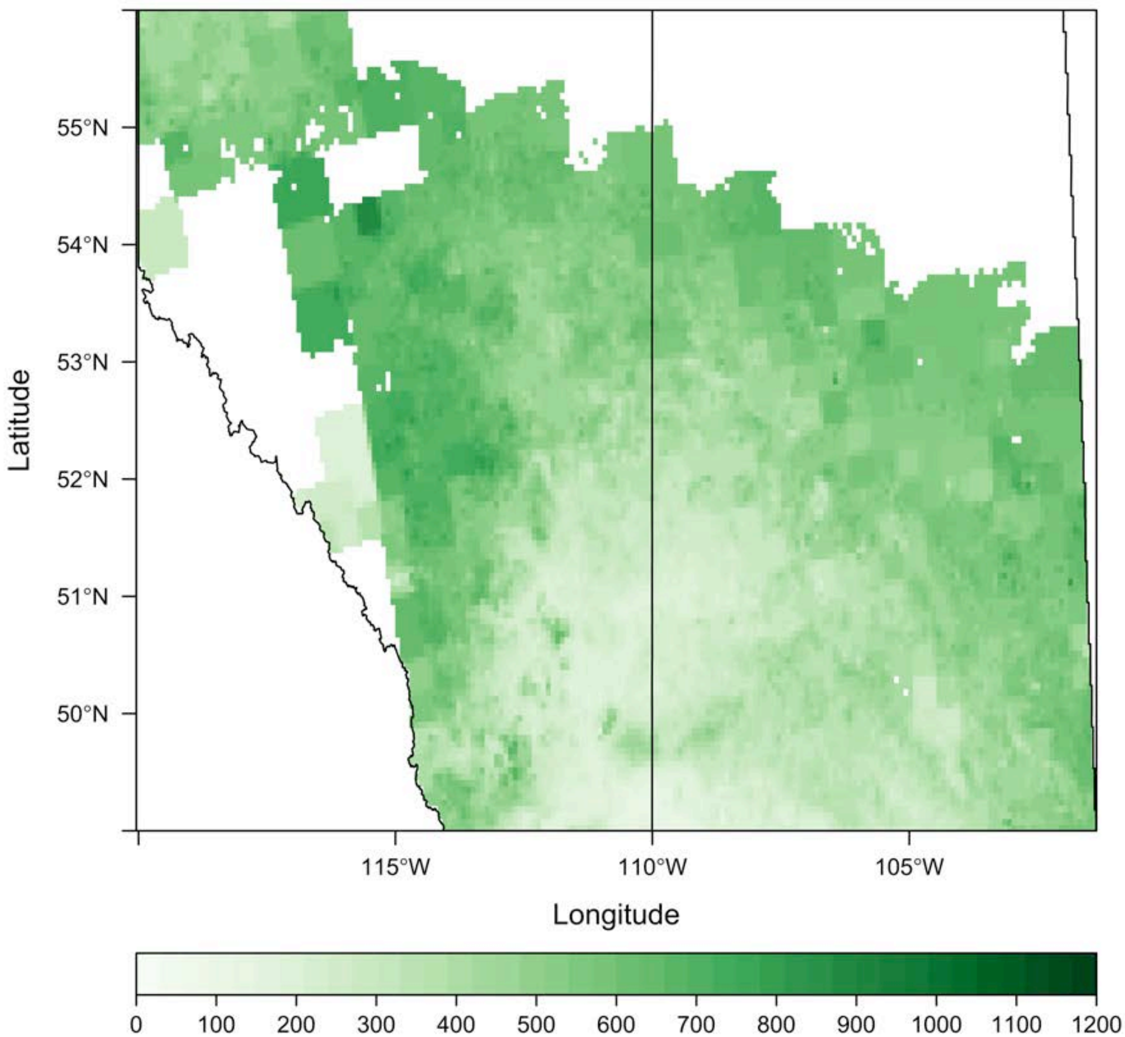

Figure 7.4: Average Values for the Airbus fAPAR Grass Production Index (GPI) for the Years 2002 - 2016 for Alberta and Saskatchewan.

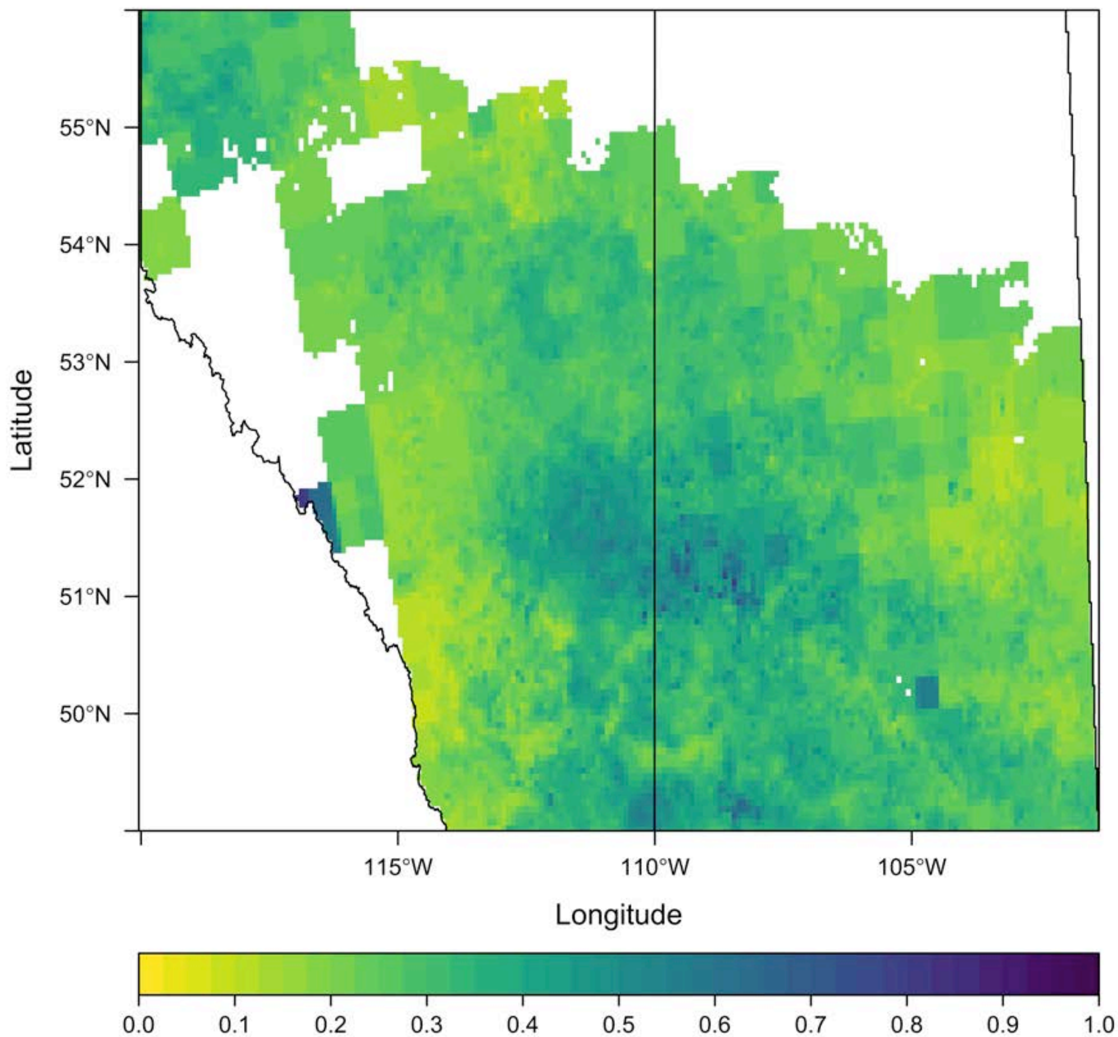

Figure 7.5: Average Coefficient of Variation (CV) for the Airbus fCover Grass Production Index (GPI) for the Years 2002 - 2016 for Alberta and Saskatchewan.

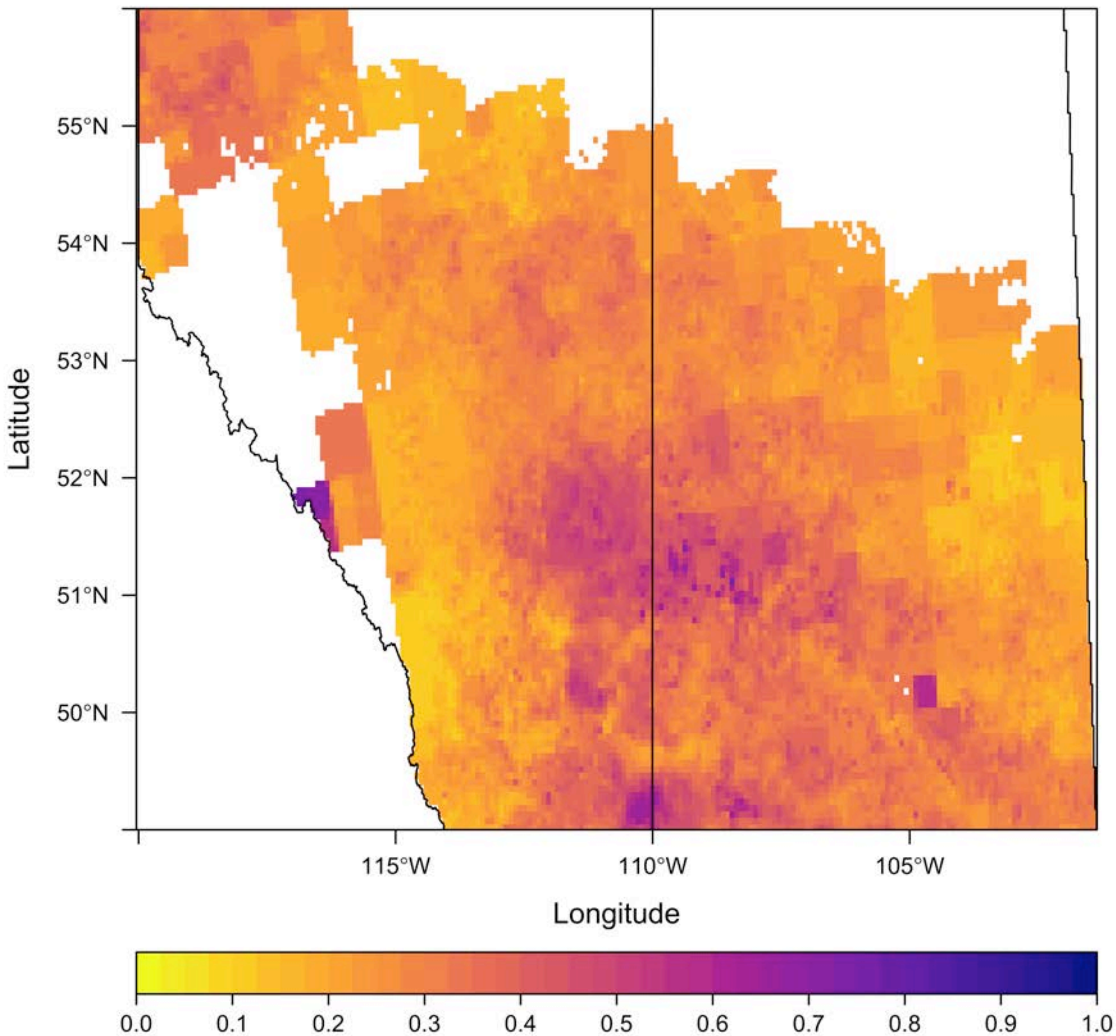

Figure 7.6: Average Coefficient of Variation (CV) for the Airbus fAPAR Grass Production Index (GPI) for the Years 2002 - 2016 for Alberta and Saskatchewan.

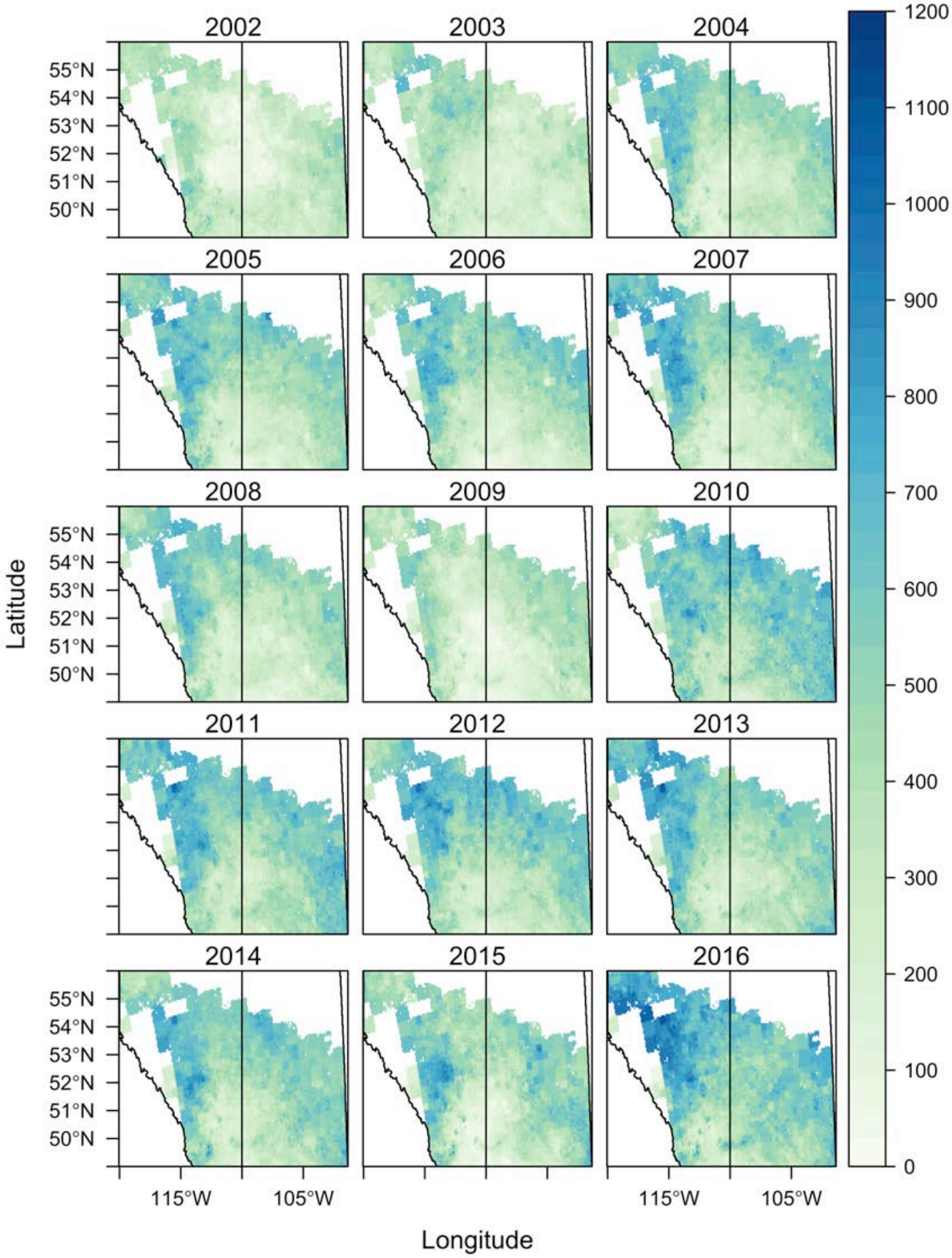

Figure 7.7: Airbus fCover Grass Production Index (GPI) for the Years 2002 - 2016 in Alberta and Saskatchewan.

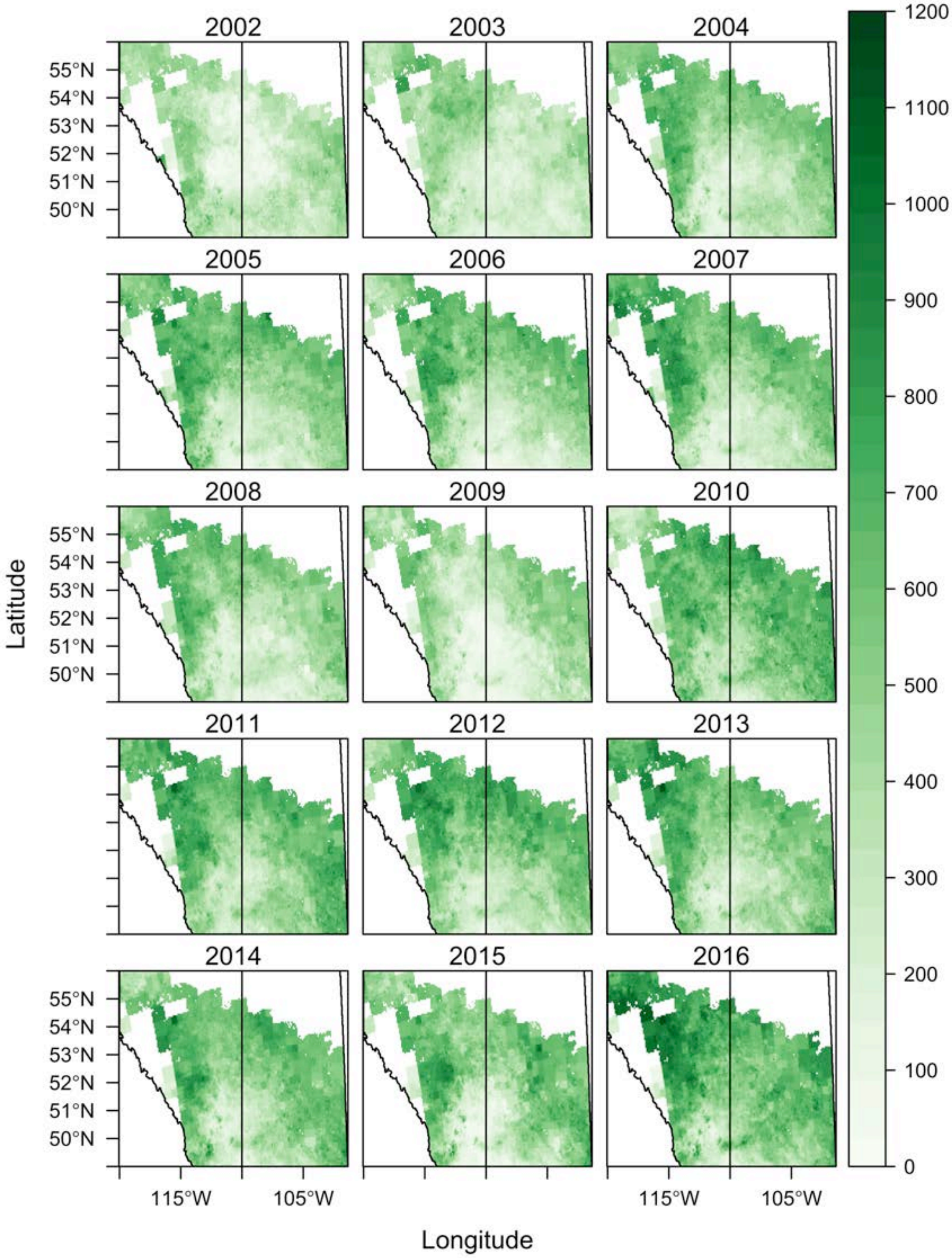

Figure 7.8: Airbus fAPAR Grass Production Index (GPI) for the Years 2002 - 2016 in Alberta and Saskatchewan.

In the figures, the average value of the Airbus fCover GPI value is shown in grey (value of 0), while the years above and below the mean are shown in green and brown, respectively. The figures suggest that deceased forage production occurred in 2002, 2003, and 2009, while there was a production increase in 2010 and 2016. It is also important to emphasize that the temporal deviation in GPI production value is only relative at the given grid cell location i, and is not relative spatially.

7.3.3. Statistical Validation Analysis of the Airbus GPI's relative to the Ground Truth Forage Yield Data

At this stage of the research project two statistical approaches to evaluate the performance of the GPI's are considered, including correlation analysis and a regression approach, which are discussed in more detail below. Figure 7.11 displays a box plot of the ground truth forage yield data in Alberta with all samples combined over the period from 2002 to 2016. It is observed that the there are a few outliers on the right tail of the distribution.

In addition, Figure 7.12 displays a box plot of the ground truth forage yield data grouped by the month of measurement (i.e. Month 6 = June and Month 8 = August) for each year from 2002 to 2016. The plot shows that in each, most years there is a large spread in values, with outliers appearing in many. August appears to have slightly more outliers. The outliers could be due to several reasons, including, for example, differences in farm management practices.

Figure 7.13 shows a box plot of the ground truth forage yield data in Saskatchewan based on the annual measurement at harvest and combined over the entire sample period from 2002 to 2015, and grouped by species, including Grass & Alfalfa, Alfalfa, and Grass only. In addition, figure 7.14 shows a box plot of the ground truth forage yield data in Saskatchewan for each of the years in the sample from 2002 to 2015. Similar to Alberta, many outliers are observed in the data.

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The correlation coefficient is one of the fundamental statistical measures that quantifies the relationship between two variables of interest. Recall that for two random variables X and Y, the (Pearson) correlation coefficient, ρ_{XY} is formally defined as

$$\rho_{XY} = \frac{Cov(X,Y)}{\sqrt{Var(X)Var(Y)}}$$

where $Var(\cdot)$ denotes the variance operator and $Cov(\cdot,\cdot)$ denotes the covariance operator. For n sample data pairs of X and Y; i.e. $(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)$, the (sample) correlation coefficient can be estimated as

$$\hat{\rho} = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}}.$$

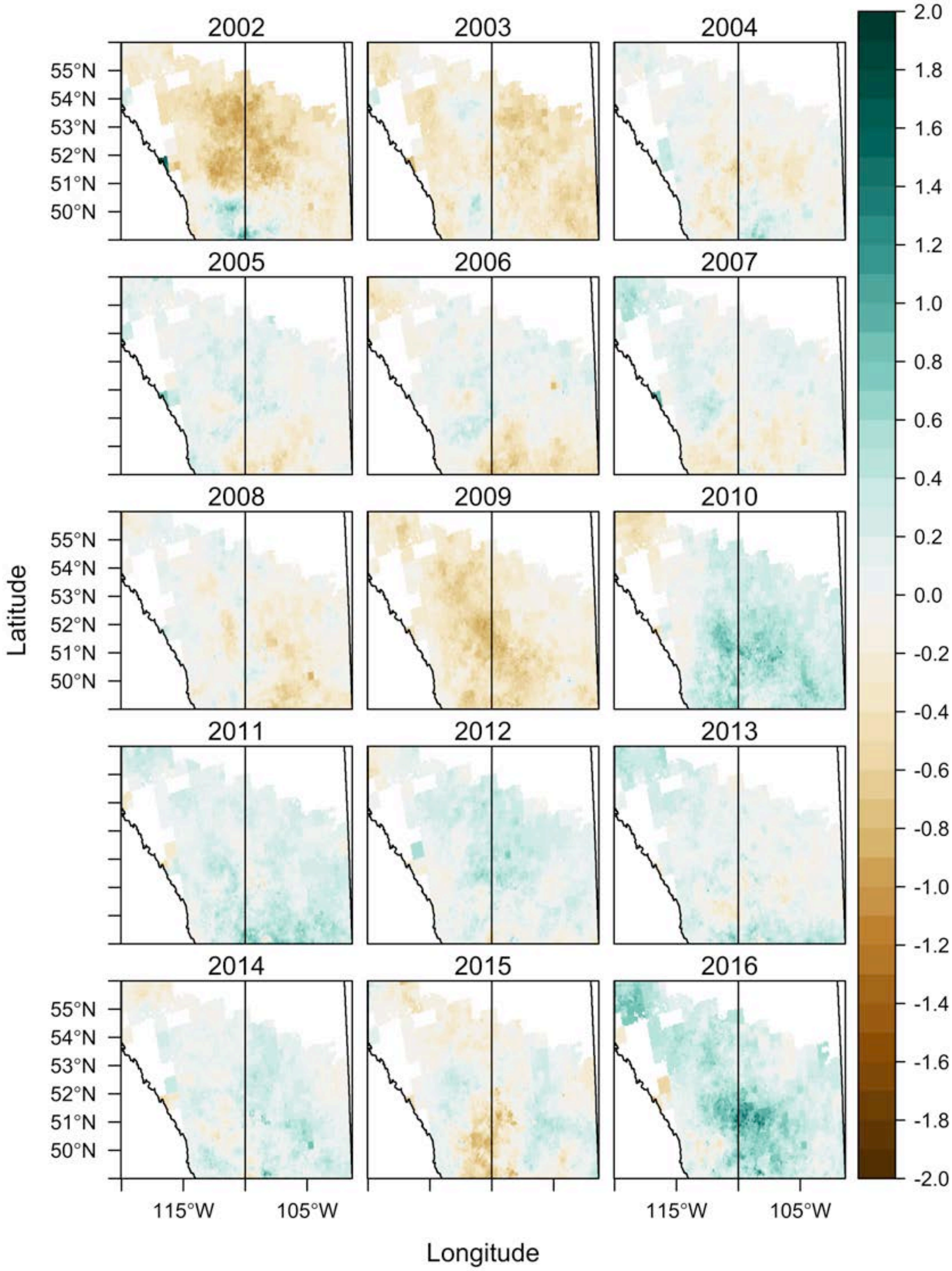


Figure 7.9: Deviation of the Value of the Airbus fCover Grass Production Index (GPI) from the Mean Value of all GPI's over the Period from 2002 to 2016 in Alberta and Saskatchewan.

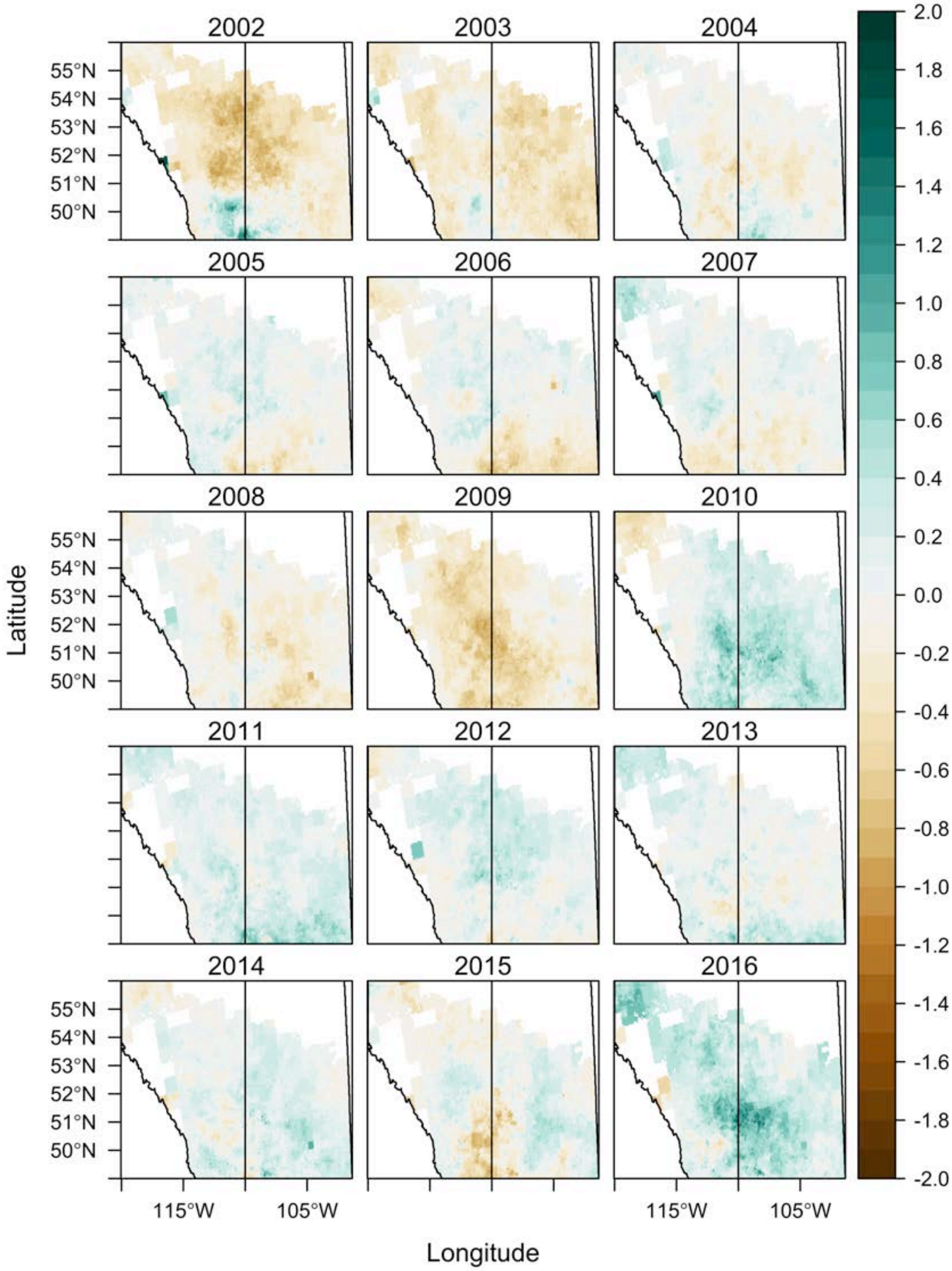


Figure 7.10: Deviation of the Value of the Airbus fAPAR Grass Production Index (GPI) from the Mean Value of all GPI's over the Period from 2002 to 2016 in Alberta and Saskatchewan.

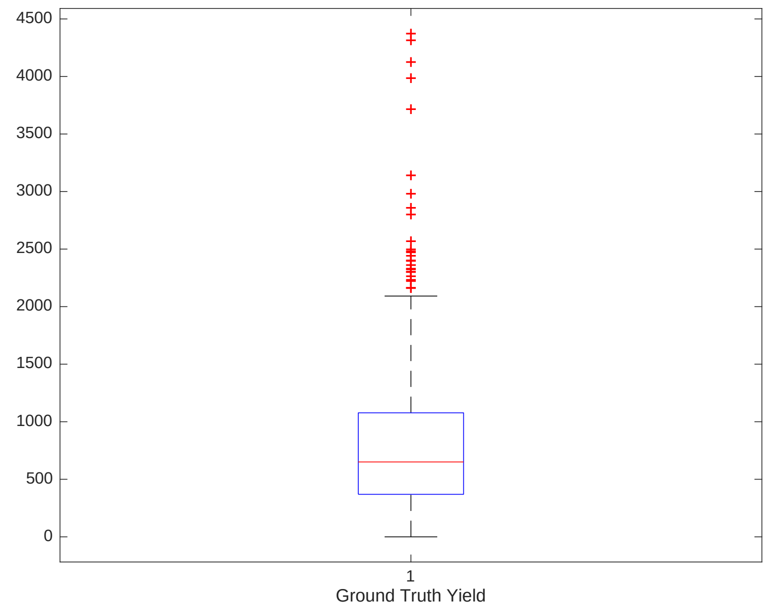


Figure 7.11: Box plot of ground truth production data in Alberta for all years combined from 2002 to 2016.

Note that $-1 \leq \rho_{XY} \leq 1$. Furthermore, both random variables are perfectly correlated for $\rho_{XY} = 1$ and perfectly negatively correlated for $\rho_{XY} = -1$. Therefore a high (positive) correlation provides a strong evidence that X is highly related to Y. (The link between correlation and regression is that for a single variable model such as used here, the correlation coefficient is the square root of the regression R^2 value. For example, a R^2 of 0.64 equals a correlation coefficient of 0.80, with sign consistent with the regression coefficient sign. Similarly, the square of the correlation coefficient gives the R^2 regression value (e.g. correlation coefficient of -0.60 gives a 0.36 R^2 regression value).

7.3.3.1. High Resolution (HR) Satellite Imagery Compared to Ground Truth Forage Yield Data

The first step in the analysis is to consider the correlation of the HR satellite imagery data to the ground truth forage yield data. This comparison between the HR GPI and the ground truth data is conducted only for the province of Alberta and not the province of Saskatchewan. This is because a relatively small number of test sites are considered in Alberta, however, in Saskatchewan many sites are considered and it can be costly to obtain the HR data.

Therefore for the province of Alberta, Airbus provided a HR fCover GPI, and the

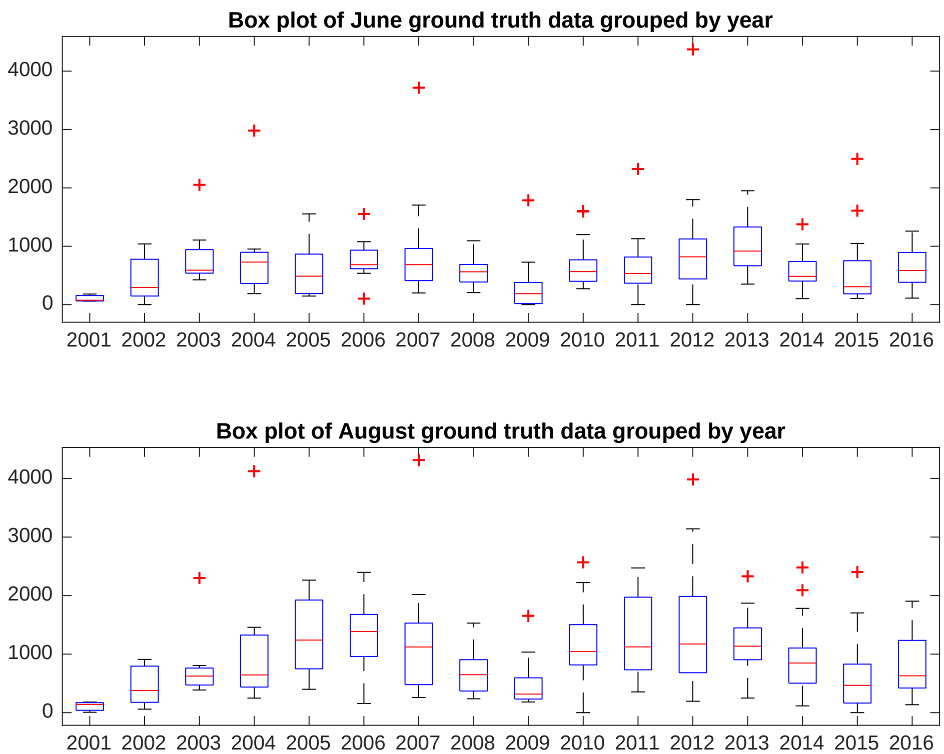


Figure 7.12: Box plot of ground truth production data in Alberta for the measurement periods in Month 6 = June and Month 8 = August and grouped by year from 2002 to 2016. The top panel corresponds to the June measurement and the bottom panel is for August.

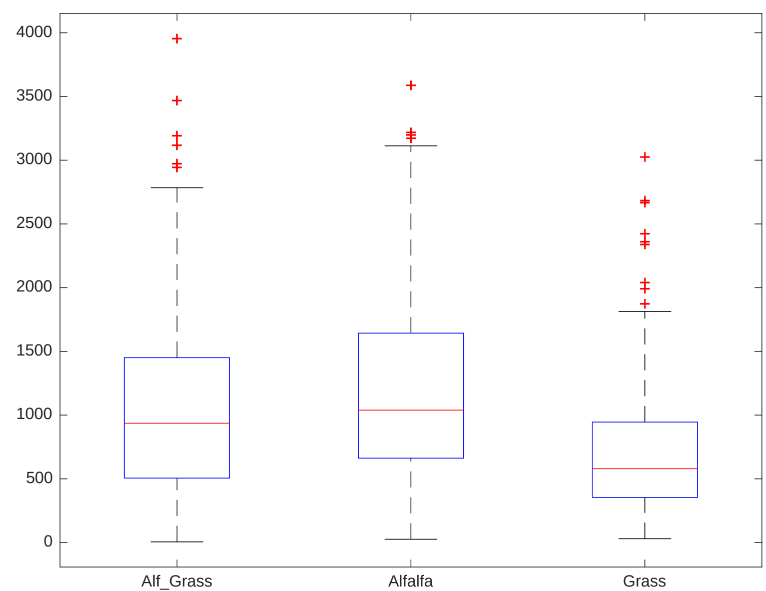


Figure 7.13: Box plot of ground truth production data in Saskatchewan based on the annual measurement at harvest and combined over the entire sample period from 2002 to 2015 (Grass & Alfalfa, Alfalfa only, and Grass only).

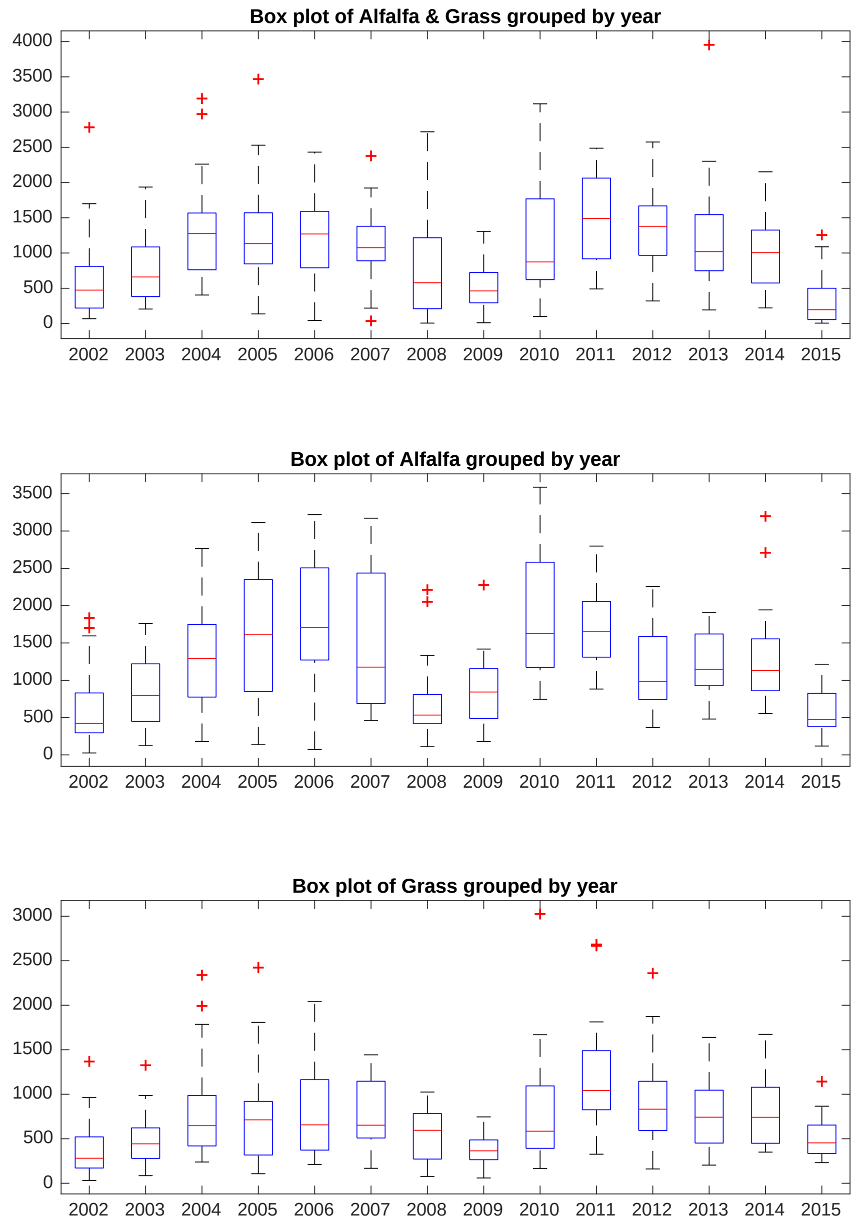


Figure 7.14: Box plot of ground truth production data in Saskatchewan annual data grouped by year (from top to bottom are figures for Grass & Alfalfa, Alfalfa only, and Grass only, respectively) from 2002 to 2015.

correlation matrix for each of the three observation periods is presented for the year 2016 in Table 7.1. The results show that the correlation coefficient between the Airbus fCover GPI and the ground truth yield data can be as high as 89.26%. It is also noted that correlations for the measurements taken in the month of June are approximately 20% lower compared to August, while correlations for the combined June & August periods are between the two. This finding is important in considering the design of the insurance product in the second phase of the research. The correlation results for the HR imagery to the ground truth forage yield data suggest that the GPI'S based on the HR data are highly related to the ground truth forage yield data, and as a result the GPI's are promising candidates for developing an index-based insurance product for forage.

Table 7.1: Correlation Matrix for the Airbus fCover GPI produced from High Resolution (HR) imagery and compared to ground truth forage yield data in Alberta for the year 2016.

		Ground Truth
June	GPI (fCover)	0.7359
August	GPI (fCover)	0.8926
June & August	GPI (fCover)	0.8442

7.3.3.2. Medium Resolution (MR) Satellite Imagery Compared to High Resolution (HR) Satellite Imagery

Next, the relationship between the GPI's generated from the MR satellite imagery is compared to the GPI's generated from the HR satellite imagery. This part of the analysis provides insight regarding the robustness of the indices at the different resolutions. It is expected that the indices produced from the different resolutions will be highly related, and this finding would provide support in using the GPI computed from the MR imagery on an operational basis.

The Airbus GPI's constructed from the HR satellite imagery have not gone through the demixing step like the GPI's produced from the MR satellite imagery. Table 7.2 displays the correlations between HR data and MR data. The results show that the HR and MR GPI is highly correlated. For example, the correlation between the MR Airbus fCover GPI and the HR Airbus fCover GPI is approximately 0.96. This provides some indication that the FPI is stable regardless of the sensor and the resolution.

Table 7.2: Correlation analysis results between the Airbus GPI's generated from the HR data and MR data.

	fCover (HR)	fCover (MR)	fAPAR (MR)
fCover (HR)	1.0000		
fCover (MR)	0.9597	1.0000	
fAPAR (MR)	0.9623	0.9978	1.0000

7.3.3.3. Medium Resolution (MR) Satellite Imagery Compared to Ground Truth Forage Yield Data

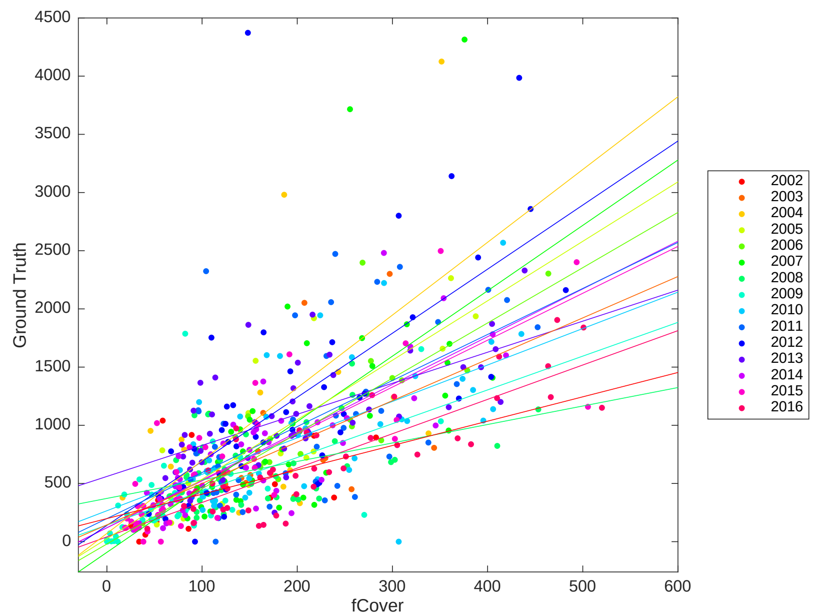
The next step in the analysis is to proceed by analyzing the relationship between the GPI's produced from the MR imagery compared to the ground truth data. This analysis is conducted for both Alberta and Saskatchewan, and is important for understanding the potential for using the GPI's generated from the MR data on an operational basis for designing the insurance product. The GPI's produced from the MR data has the advantage of being more cost effective with more frequent observations compared to the HR satellite imagery data.

7.3.3.4. Scatterplots of the Medium Resolution (MR) Satellite Imagery Compared to Ground Truth Forage Yield Data

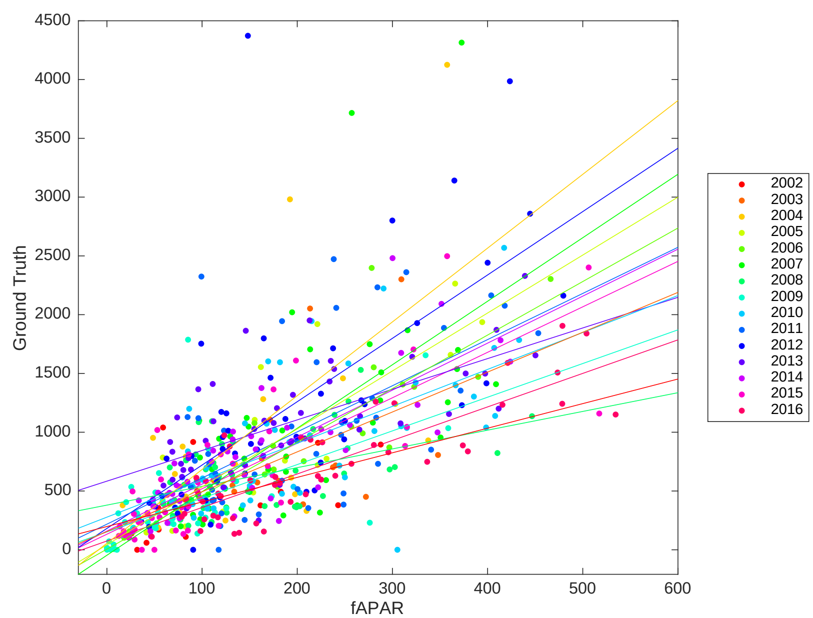
Scatterplots of the Airbus MR fCover and fAPAR GPI's are examined for the provinces of Alberta and Saskatchewan. First, the Airbus fCover and fAPAR GPI's in Alberta are plotted against the ground truth data and grouped by year for each period in the sample from 2002 to 2016 as shown in Figure 7.15. The first plot is for the fCover GPI and the second plot is for the fAPAR GPI. Overall, the results show a positive and increasing relationship between the GPI and the ground truth yield data. As well, the plots show variation across the years.

In addition to examining the scatterplots by year, it is also interesting to view the plots grouped by the measurement period, which is shown in Figure 7.16. The two measurement periods correspond to June and August, and include observations across all of the sample years from 2002 to 2016. The first plot is for the fCover GPI and the second plot is for the fAPAR GPI. Overall, the results show that the August measurement of the ground truth forage yield data has higher correlation with both GPI's.

Next, the Airbus GPI's are plotted against the ground truth forage yield data for the province of Saskatchewan. Figure 7.17 is for the Airbus Grass & Alfalfa GPI, and the first plot is for fCover, the second plot is for fAPAR. Figure 7.18 is for the Airbus Alfalfa GPI, and the first plot is for fCover, the second plot is for fAPAR. Figure 7.19 is for the Airbus Grass GPI, and the first plot is for fCover, the second plot is for fAPAR.

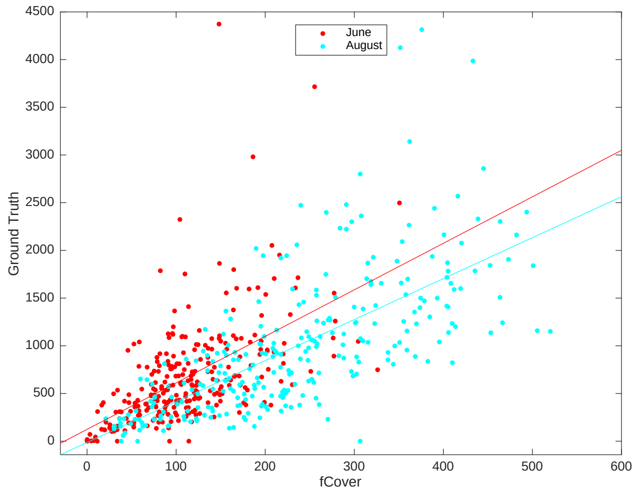


(a) fCover against ground truth data grouped by year.

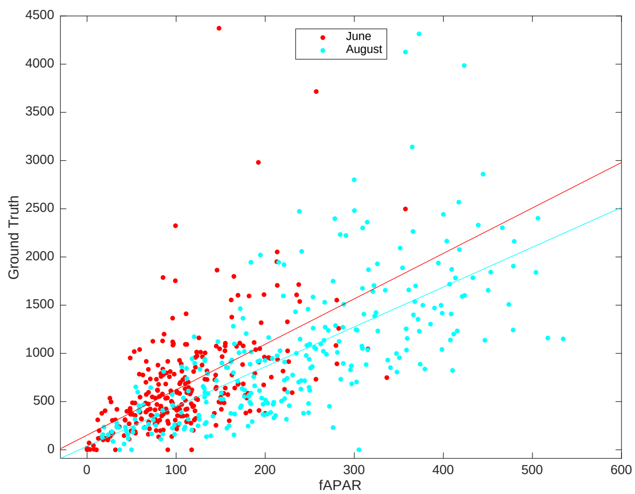


(b) fAPAR against ground truth data grouped by year.

Figure 7.15: Scatterplots of the MR GPI against ground truth production data grouped by year for the province of Alberta. The figures show scatterplots of the Airbus fCover GPI and fAPAR GPI, respectively, against ground truth production data grouped by year over the period 2002 to 2016.

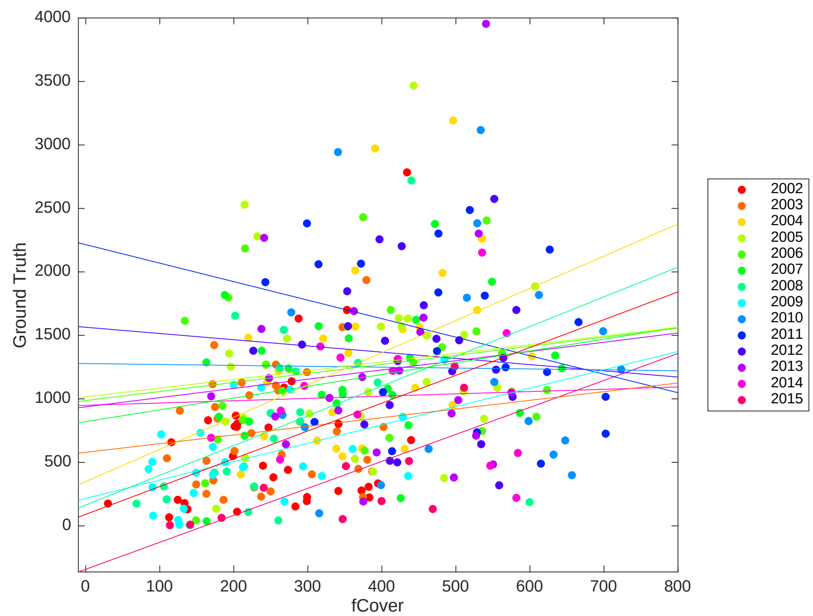


(a) fCover against ground truth data grouped by cutting month.

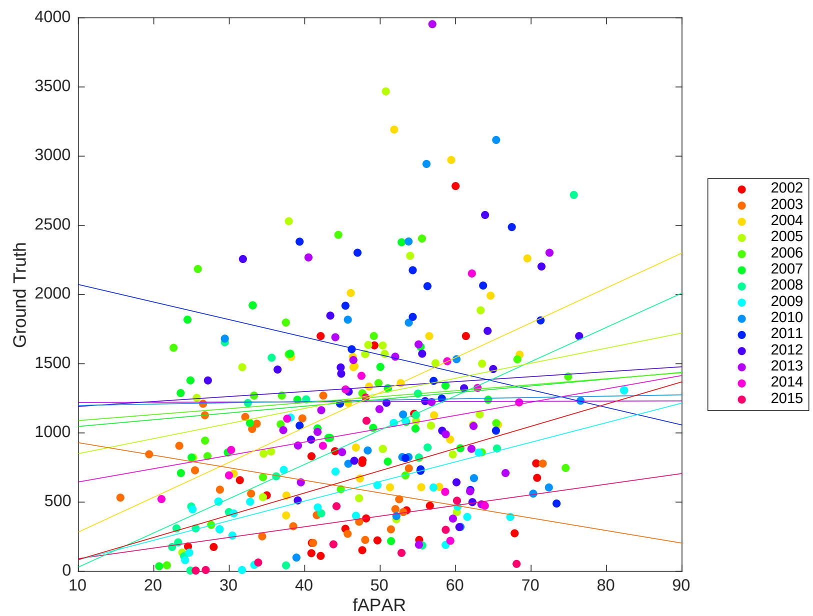


(b) fAPAR against ground truth data grouped by cutting month.

Figure 7.16: Scatterplots of the MR GPI against ground truth production data grouped by cutting month for the province of Alberta. The first plot (a) shows the fCover GPI, and the second plot (b) shows the fAPAR GPI.

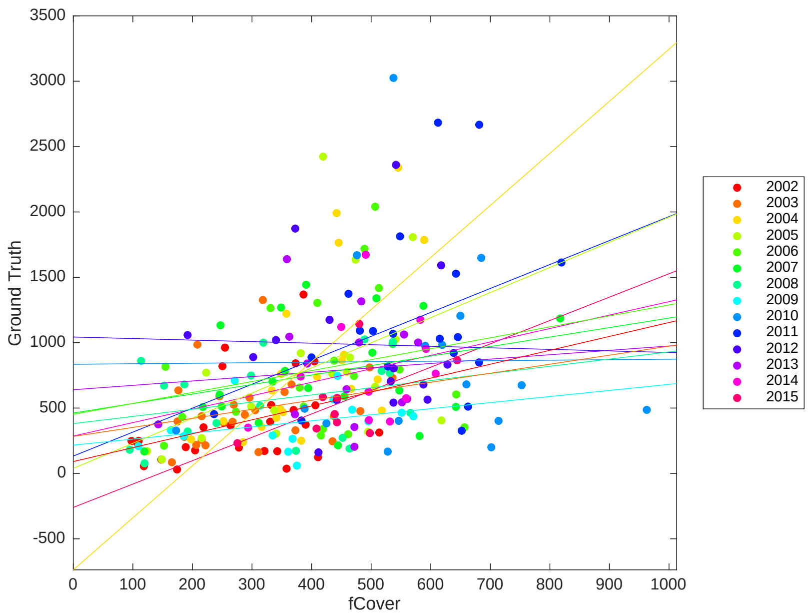


(a) Airbus fCover GPI against ground truth data in SK for Grass & Alfalfa by year.

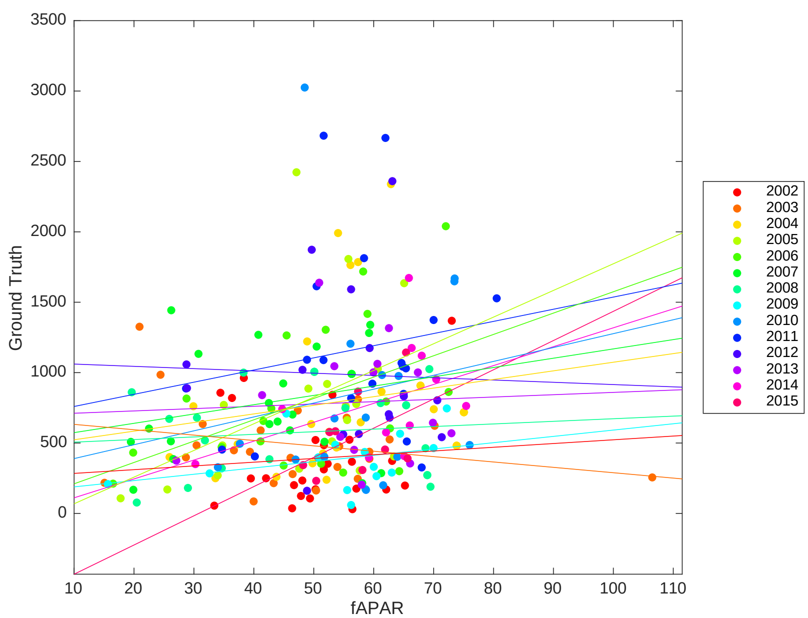


(b) Airbus fARPAR GPI against ground truth data in SK for Grass & Alfalfa by year.

Figure 7.17: Scatterplots of the MR Airbus GPI against ground truth forage yield data in Saskatchewan grouped by year over the period from 2002 to 2015. The first plot shows the fCover GPI for Grass & Alfalfa, and the second plot shows the fAPAR GPI for Grass & Alfalfa.

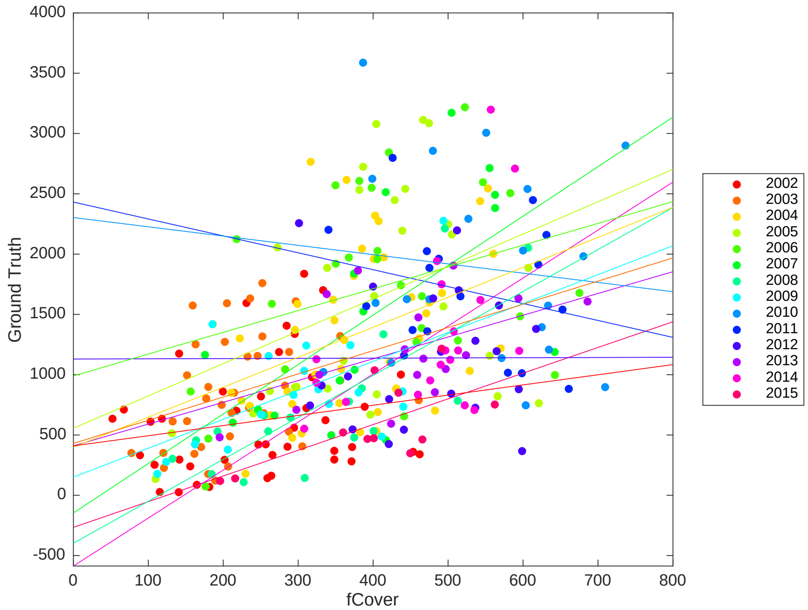


(a) Airbus fCover GPI against ground truth data in SK for Grass by year.

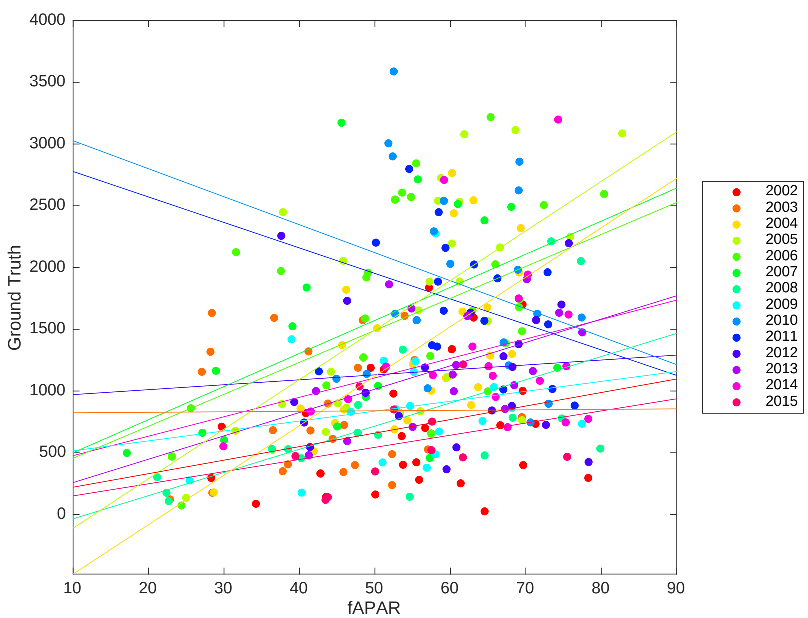


(b) Airbus fARPAR GPI against ground truth data in SK for Grass by year.

Figure 7.18: Scatterplots of the MR Airbus GPI against ground truth forage yield data in Saskatchewan grouped by year over the period from 2002 to 2015. The first plot shows the fCover GPI for Grass, and the second plot shows the fAPAR GPI for Grass.



(a) Airbus fCover GPI against ground truth data in SK for Alfalfa by year.



(b) Airbus fARPAR GPI against ground truth data in SK for Alfalfa by year.

Figure 7.19: Scatterplots of the MR Airbus GPI against ground truth forage yield data in Saskatchewan grouped by year over the period from 2002 to 2015. The first plot shows the fCover GPI for Alfalfa, and the second plot shows the fAPAR GPI for Alfalfa.

As with the Alberta results, the plots for Saskatchewan show correlation variations across the years. For a few of the years in Saskatchewan, negative correlations are observed. This may be due to some of the limitations previously discussed with the ground truth forage yield data, including the uncertainty of the measurement dates and how these align with the index values, for example. Overall, however, the plots show a positive and increasing relationship between the GPI's and the ground truth forage yield data. In addition, it is observed that in more recent years the correlation results are much stronger. Note that the ground truth data considered in Saskatchewan only has one measurement period at harvest.

7.3.3.5. Correlation Matrix of the Medium Resolution (MR) Satellite Imagery Compared to Ground Truth Forage Yield Data

In addition to viewing plots of the Airbus GPI's relative to the ground truth data, a correlation matrix for each province can also be generated. For Alberta, Table 7.3 shows the Airbus fCover and fAPAR GPI's generated from the MR imagery and compared to the ground truth data across all test sites. The results highlight the correlations for the most recent year in the sample data, 2016. As well, the overall correlation results are provided using data from the entire sample period from 2002 to 2016. The results for the most recent 2016 observation period show that the correlation coefficient between the Airbus MR fCover GPI and the ground truth yield data can be as high as 89.86%, and 90.62% for the Airbus fCover GPI, and fAPAR GPI, respectively using the August measurement period. The correlations using June as the measurement period are lower at 71.36% for fCover and 64.24% for fAPAR. The correlation results for the combined June & August period are between the two at 83.30% for fCover and 78.86% for fAPAR. Overall across all of the measurement periods, fCover has a higher correlation compared to fAPAR. The overall results show slightly lower correlations than the most recent years. fCover correlations are higher than fARPAR for the June and June & August measurements, and are lower than fARPAR for the August measurement.

As with Alberta, the correlations for the MR Airbus fCover and fAPAR GPI's relative to the ground truth data in Saskatchewan are examined. with the results for the most recent year, 2015, as well as the overall results for the entire sample period from 2002 to 2015 shown in Table 7.4. Overall, the results show that the Airbus fCover GPI tends to be more highly correlated with the ground truth forage yield data compared to the fAPAR GPI. The results for the most recent 2015 observation period show that the correlation coefficient between the Airbus MR fCover GPI and the ground truth yield data can be as high as 70.84% for Grass&Alfalfa, and 44.78% for the fAPAR GPI for Grass. Overall, Grass&Alfalfa has a correlation coefficient of of 35.63% for fCover, and 26.01% for fAPAR. For Alfalfa the correlation is 48.55% for fCover, and 34.43% for fAPAR, while for Grass the correlation is 39.88% for fCover, and 19.10% for fAPAR.

Table 7.3: Correlation Matrix for the MR Airbus fCover and fAPAR GPI's and the ground truth forage yield data for Alberta for the most recent year, as well as over the whole sample period. Results for both fCover and fAPAR are shown for the measurement periods of June (Season start - June 30), August (Season start - August 15), and June & August combined.

		Most Recent Year	**Overall**
June & August	GPI (fCover)	0.8330	0.6543
	GPI (fAPAR)	0.7886	0.6075
June	GPI (fCover)	0.7136	0.5577
	GPI (fAPAR)	0.6424	0.4969
August	GPI (fCover)	0.8986	0.6899
	GPI (fAPAR)	0.9062	0.6916

Table 7.4: Correlation Matrix for the MR Airbus fCover and fAPAR GPI's and the ground truth forage yield data for Saskatchewan. The table shows results for the most recent year and overall results. Results for both fCover and fAPAR are shown for Grass & Alfalfa, Alfalfa, and Grass.

		Most Recent Year	**Overall**
Grass & Alfalfa	GPI (fCover)	0.7084	0.3563
	GPI (fAPAR)	0.2049	0.2601
Alfalfa	GPI (fCover)	0.6687	0.4855
	GPI (fAPAR)	0.2939	0.3443
Grass	GPI (fCover)	0.5866	0.3988
	GPI (fAPAR)	0.4478	0.1910

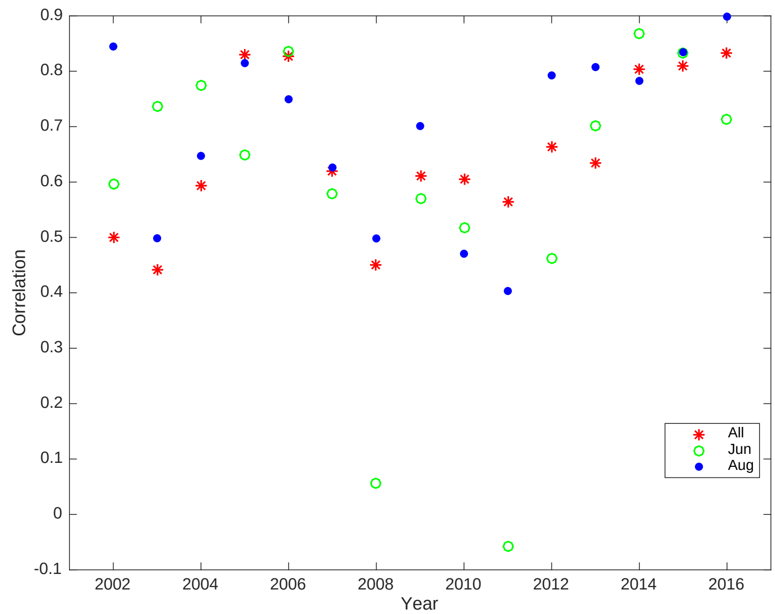
7.3.3.6. *Robustness Check of Correlations of the Medium Resolution (MR) Satellite Imagery Compared to Ground Truth Forage Yield Data*

In order to understand the robustness of the Airbus fCover and fAPAR GPI'S in Alberta and Saskatchewan, the correlations with the ground truth forage yield data are also calculated for each year over the sample period. Table 7.5 shows the Airbus fCover GPI results for Alberta from 2002 to 2016, and Table 7.6 shows the Airbus fAPAR GPI results for Alberta from 2002 to 2016. In addition, Figure 7.20 plots the correlation results of the Airbus MR fCover and fAPAR GPI's by each year and measurement period for the province of Alberta.

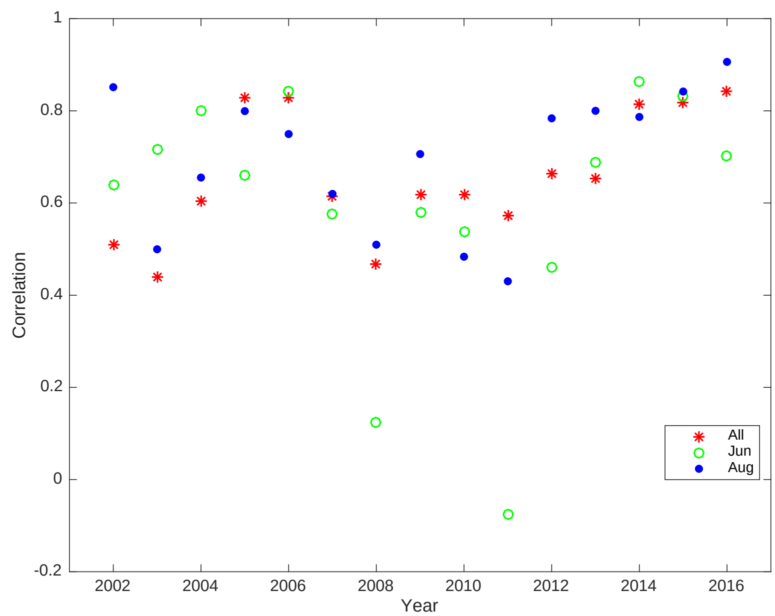
Table 7.5: Robustness check with correlations of the MR Airbus fCover GPI compared to the ground truth forage yield data in Alberta by year and measurement period.

Month	**Year**	**Correlation**	**Year**	**Correlation**	**Year**	**Correlation**
Jun & Aug	2002	0.4989	2007	0.6188	2012	0.6627
Jun	2002	0.5977	2007	0.5776	2012	0.4618
Aug	2002	0.8446	2007	0.6262	2012	0.7925
Jun & Aug	2003	0.4405	2008	0.4491	2013	0.6347
Jun	2003	0.7357	2008	0.0570	2013	0.7006
Aug	2003	0.4985	2008	0.4982	2013	0.8075
Jun & Aug	2004	0.5921	2009	0.6105	2014	0.8045
Jun	2004	0.7738	2009	0.5696	2014	0.8664
Aug	2004	0.6472	2009	0.7011	2014	0.7826
Jun & Aug	2005	0.8312	2010	0.6055	2015	0.8107
Jun	2005	0.6489	2010	0.5177	2015	0.8324
Aug	2005	0.8146	2010	0.4706	2015	0.8344
Jun & Aug	2006	0.8263	2011	0.5650	2016	0.8330
Jun	2006	0.8351	2011	-0.0591	2016	0.7136
Aug	2006	0.7494	2011	0.4033	2016	0.8986

Overall, there is variation in the correlation results across the various years. The fCover and fAPAR GPI'S are highly related showing the strongest correlations in the same years, and the weakest correlations in the same years. In general, the fCover GPI seems to slightly out perform the fAPAR GPI. It appears that the correlation results are strongest in the more recent years, including 2014, 2015 and 2016. The years with the lowest correlations are in 2003, 2008 and 2011. It can also be observed that the measurement period in August normally has the highest correlation, and the measurement period in June the lowest correlation, however, this is not always the case. For example, in 2004 June has the highest correlation for both the fCover and fAPAR



(a) MR Airbus fCover correlation results by year and measurement period.



(b) MR Airbus fAPAR correlation results by year and measurement period.

Figure 7.20: Correlation results for each year by measurement period for Alberta. The first plot is for the MR Airbus fCover GPI, and the second figure is for the MR Airbus fAPAR GPI.

Table 7.6: Robustness check with correlations of the MR Airbus fAPAR GPI compared to the ground truth forage yield data in Alberta by year and measurement period.

Month	Year	Correlation	Year	Correlation	Year	Correlation
Jun & Aug	2002	0.3958	2007	0.5567	2012	0.5999
Jun	2002	0.2026	2007	0.5721	2012	0.3459
Aug	2002	0.8513	2007	0.6197	2012	0.7837
Jun & Aug	2003	0.3075	2008	0.4423	2013	0.5443
Jun	2003	0.7158	2008	-0.0378	2013	0.6548
Aug	2003	0.4996	2008	0.5095	2013	0.8000
Jun & Aug	2004	0.5050	2009	0.5519	2014	0.7607
Jun	2004	0.7998	2009	0.4374	2014	0.8210
Aug	2004	0.6552	2009	0.7062	2014	0.7867
Jun & Aug	2005	0.7998	2010	0.5905	2015	0.7716
Jun	2005	0.6380	2010	0.5310	2015	0.8195
Aug	2005	0.7994	2010	0.4835	2015	0.8419
Jun & Aug	2006	0.8025	2011	0.5837	2016	0.7886
Jun	2006	0.8628	2011	-0.1128	2016	0.6424
Aug	2006	0.7496	2011	0.4302	2016	0.9062

GPI's. Further investigation is needed in years 2008 and 2011 in particular. The years with the lowest correlations may be due to some of the limitations of the ground truth forage yield data discussed previously, including the timing of the measurement, for example.

Similarly, the robustness of the Airbus fCover and fAPAR GPI'S in Saskatchewan are examined, and the correlations with the ground truth forage yield data are calculated for each year over the sample period. Table 7.7 shows the Airbus fCover GPI results for Saskatchewan from 2002 to 2015, and Table 7.8 shows the Airbus fAPAR GPI results for Saskatchewan from 2002 to 2015. In addition, Figure 7.21 plots the correlation results of the Airbus MR fCover and fAPAR GPI's by each year and species for Saskatchewan.

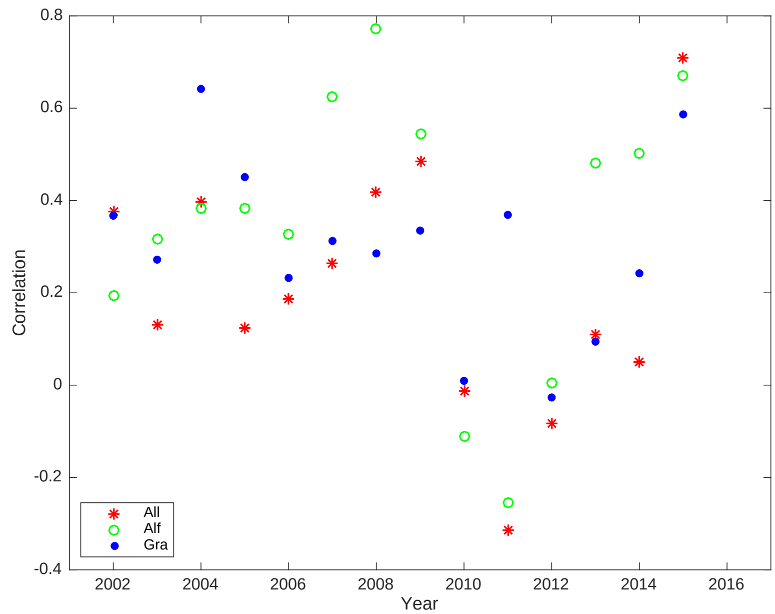
The results show except for a few years, overall, Alfalfa has the highest correlations among all species. For the year 2015 for fCover, and 2009 for fARPAR, Grass & Alfalfa has stronger correlations. Specifically, the correlation coefficient between the Airbus fCover GPI and the ground truth yield data can be as high as 70.84% for Grass &Alfalfa (in 2015). As is also observed from the scatter plots in Figure 7.21, there are some years displaying negative correlations, such as in years 2010, 2011, and 2012. This may due to the sampling issue of the data, or other limitations previously discussed. However, it is noted that the most recent year in the observation period, 2015, shows stronger correlations. The results from the Airbus fAPAR GPI shows similar information, with the correlation coefficient between the Airbus fAPAR GPI and the ground truth yield data as high as 44.78% for Grass (in 2015). As is also observed from the scatter plots in Figure 7.21, there are some years displaying negative correlations, such as in years 2003, 2010, and 2011.

Table 7.7: Correlation Matrix for the MR Airbus fCover GPI and the ground truth forage yield data for Saskatchewan for each of the years in the sample period from 2002 to 2015. Results are shown for species, including Grass & Alfalfa, Alfalfa, and Grass.

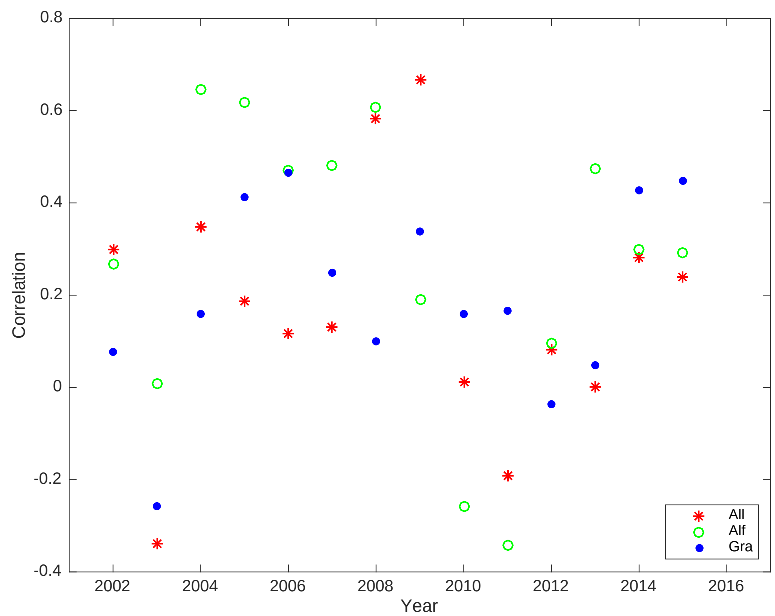
Month	Year	Correlation	Year	Correlation	Year	Correlation
Grass & Alfalfa	2002	0.3753	2007	0.2646	2012	-0.0816
Alfalfa	2002	0.1933	2007	0.6241	2012	0.0032
Grass	2002	0.3671	2007	0.3124	2012	-0.0267
Grass & Alfalfa	2003	0.1325	2008	0.4177	2013	0.1091
Alfalfa	2003	0.3156	2008	0.7708	2013	0.4815
Grass	2003	0.2719	2008	0.2854	2013	0.0943
Grass & Alfalfa	2004	0.3957	2009	0.4839	2014	0.0485
Alfalfa	2004	0.3817	2009	0.5447	2014	0.5038
Grass	2004	0.6417	2009	0.3349	2014	0.2423
Grass & Alfalfa	2005	0.1249	2010	-0.0123	2015	0.7084
Alfalfa	2005	0.3841	2010	-0.1109	2015	0.6687
Grass	2005	0.4507	2010	0.0093	2015	0.5866
Grass & Alfalfa	2006	0.1880	2011	-0.3153		
Alfalfa	2006	0.3265	2011	-0.2557		
Grass	2006	0.2323	2011	0.3689		

7.3.3.7. Scenario Analysis of Correlations of the Medium Resolution (MR) Satellite Imagery Compared to Ground Truth Forage Yield Data

In addition to the correlation analysis above based on all of the yield observations within the sample period, it is also interesting to perform a scenario analysis to consider the results for exceptionally high and exceptionally low years. For each test site location, exceptionally high years are defined as the years with the GPI values greater than 90% of the quantile of the same location, while the exceptionally low years are defined as the years with the GPI values smaller than the 10% quantile. The remaining years are considered normal years. The performance of the indices for the bad years are important as they correspond to the situations in which an insurance payment would be expected. It is these years that it is important for the index to accurately reflect this loss to ensure an appropriate indemnity payment to the producer. However, it is important to recognize that the other scenarios, including good and normal forage yields, should



(a) MR Airbus fCover correlation results by year for species.



(b) MR Airbus fAPAR correlation results by year for species.

Figure 7.21: Correlation results for each year for species in Saskatchewan, including Grass & Alfalfa, Alfalfa, and Grass. The first plot is for the MR Airbus fCover GPI, and the second figure is for the MR Airbus fAPAR GPI.

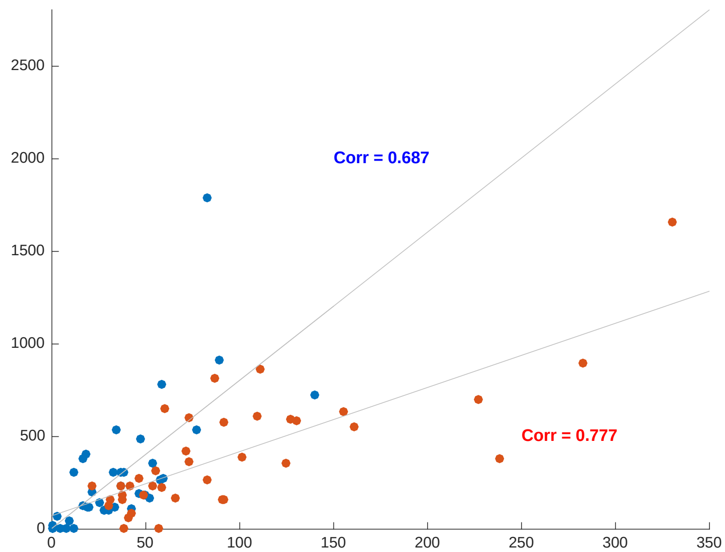
Table 7.8: Correlation Matrix for the MR Airbus fAPAR GPI and the ground truth forage yield data for Saskatchewan for each of the years in the sample period from 2002 to 2015. Results are shown for species, including Grass & Alfalfa, Alfalfa, and Grass.

Month	**Year**	**Correlation**	**Year**	**Correlation**	**Year**	**Correlation**
Grass & Alfalfa	2002	0.3004	2007	0.1296	2012	0.0801
Alfalfa	2002	0.2684	2007	0.4801	2012	0.0953
Grass	2002	0.0770	2007	0.2486	2012	-0.0364
Grass & Alfalfa	2003	-0.3385	2008	0.5844	2013	0.0017
Alfalfa	2003	0.0089	2008	0.6079	2013	0.4728
Grass	2003	-0.2575	2008	0.0999	2013	0.0481
Grass & Alfalfa	2004	0.3463	2009	0.6655	2014	0.2816
Alfalfa	2004	0.6445	2009	0.1910	2014	0.2993
Grass	2004	0.1593	2009	0.3380	2014	0.4273
Grass & Alfalfa	2005	0.1866	2010	0.0127	2015	0.2409
Alfalfa	2005	0.6184	2010	-0.2593	2015	0.2935
Grass	2005	0.4125	2010	0.1592	2015	0.4478
Grass & Alfalfa	2006	0.1156	2011	-0.1924		
Alfalfa	2006	0.4692	2011	-0.3424		
Grass	2006	0.4653	2011	0.1661		

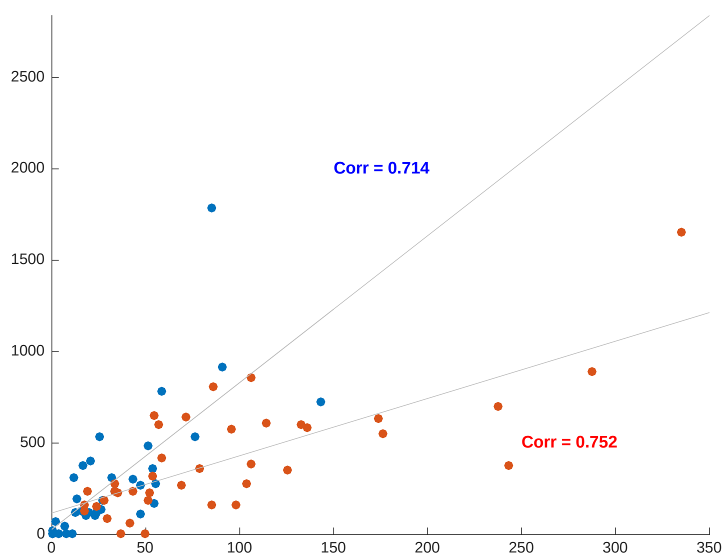
also be strongly related to the index because these estimated yields contribute to the overall yield history that is necessary to offer an index-based insurance product.

Figure 7.22, Figure 7.23, and Figure 7.24 show the scatterplots of exceptionally low, exceptionally high, and normal years, respectively, in Alberta. Figure 7.22 shows that the exceptionally low years correlations between the ground truth forage yield data and the Airbus fCover and fAPAR GPI's are the strongest, with results 0.687 for June and 0.777 for August for fCover, and 0.714 for June and 0.752 for August for fAPAR. The exceptionally high yields have correlations of 0.575 for June and 0.544 for August for the Airbus fCover GPI, and correlations of 0.568 for June and 0.582 for August for the Airbus fAPAR GPI. For normal years, the correlations are 0.500 for June and 0.665 for August for the Airbus fCover GPI, and correlations of 0.524 for June and 0.668 for August for the Airbus fAPAR GPI.

Similar scenario analysis is also performed for the province of Saskatchewan. Figure 7.25, Figure 7.26, and Figure 7.27 show the scatterplots of exceptionally high low, exceptionally high, and normal yields, respectively. Figure 7.25 shows that the correlations of the exceptionally low yields and the Airbus fCover and fAPAR GPI's are the strongest. The results are as high as 0.558 for Grass&Alfalfa. 0.32 for Alfalfa, and 0.460 for Grass for fCover, while correlations are 0.300 for Grass&Alfalfa, 0.219 for Alfalfa, and 0.326 for Grass in the case of fAPAR. The exceptionally high yields have correlations of 0.162 for Grass&Alfalfa, 0.145 for Alfalfa, and 0.294 for Grass in

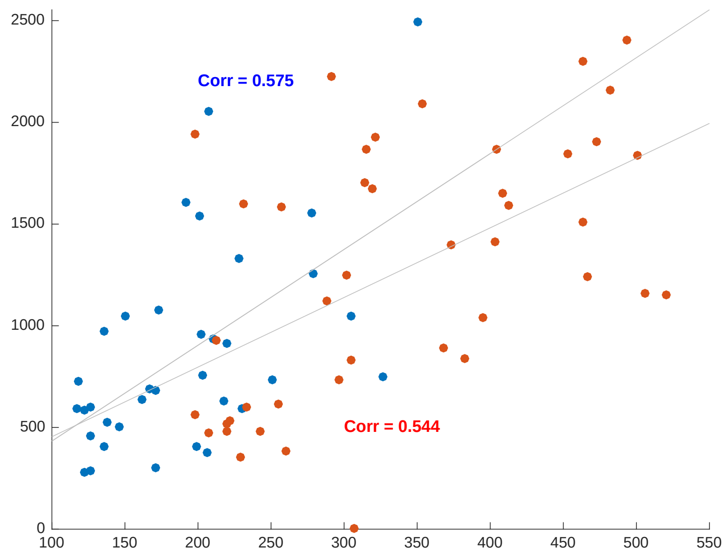


(a) Airbus fCover GPI scatterplot of exceptionally low yields in Alberta, which are defined as the years with the GPI values lower than the 10% quantile.

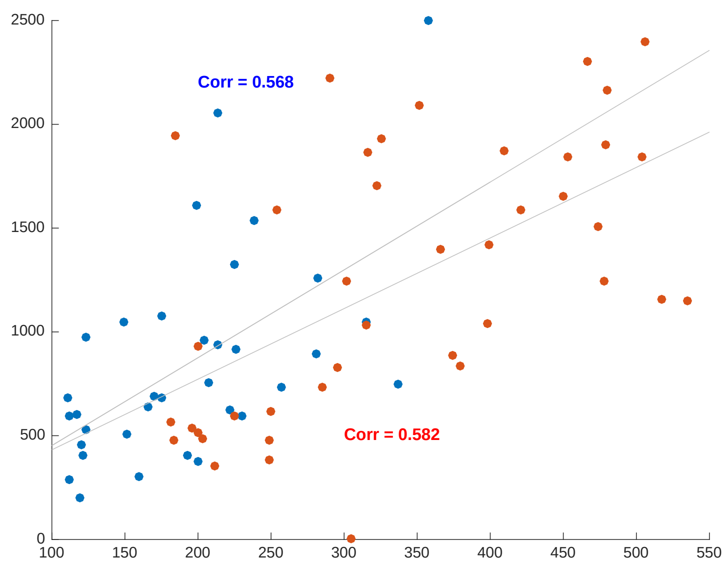


(b) Airbus fAPAR GPI scatterplot of exceptionally low yields in Alberta, which are defined as the years with the GPI values lower than the 10% quantile.

Figure 7.22: Scatter plot of bad years. The figures show scatterplots of exceptionally low yields in Alberta based on scenario analysis. The first figure shows the scatter plot of fCover, and the second figure shows the scatter plot of fAPAR. Blue and red dots represent the measurement periods of June and August, respectively.

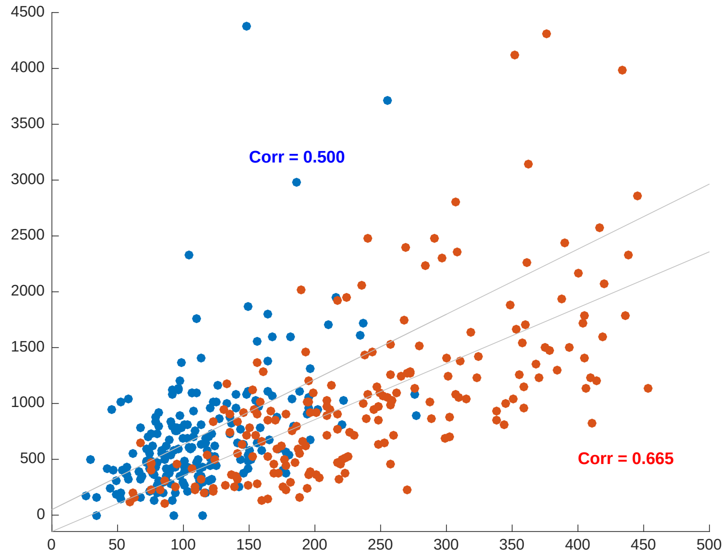


(a) Airbus fCover GPI scatterplot of above exceptionally high yields in Alberta, which are defied as the years with the GPI values higher than the 90% quantile.

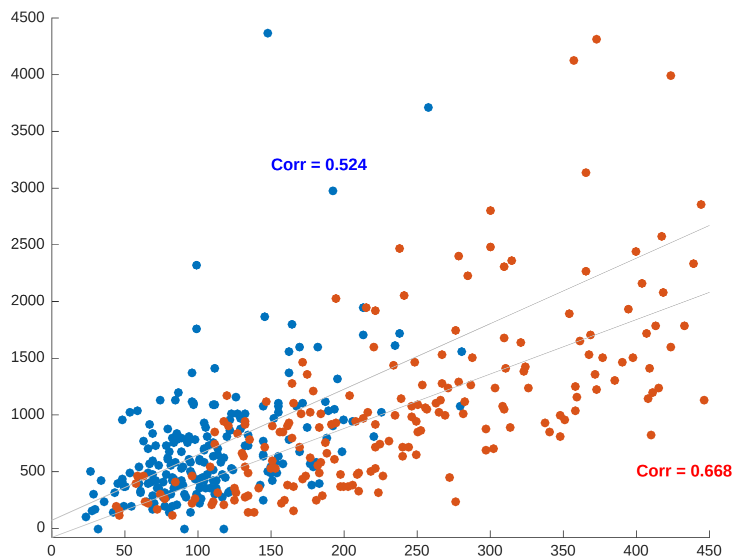


(b) Airbus fAPAR GPI scatterplot of exceptionally highyields in Alberta, which are defied as the years with the GPI values higher than the 90% quantile.

Figure 7.23: Scatter plot of good years. The figures show scatterplots of the exceptionally high yields in Alberta based on scenario analysis. The first figure shows the Airbus fCover GPI, and the second figure shows the Airbus fAPAR GPI. Blue and red dots represent the measurement periods of June and August, respectively.



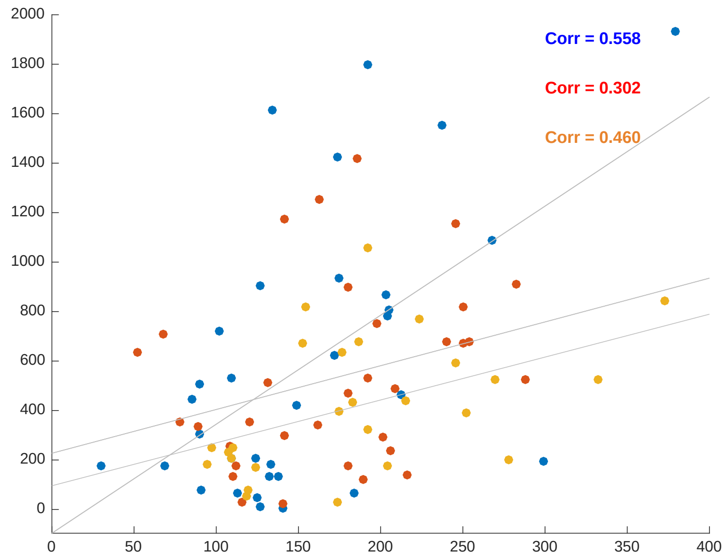
(a) Airbus fCover GPI scatterplot of normal forage yields in Alberta.



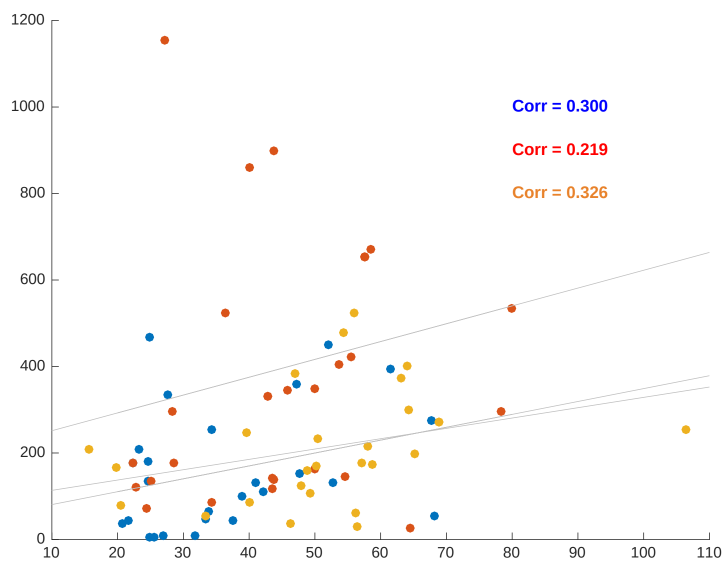
(b) Airbus fAPAR GPI scatterplot of normal forage yields in Alberta.

Figure 7.24: Scatter plot of normal years. The figures show scatterplot of the normal forage yields in Alberta based on scenario analysis. The first figure shows the Airbus fCover GPI, and the second figure shows the Airbus fAPAR GPI. Blue and red dots represent the measurement periods of June and August, respectively.

the case of fCover, and 0.228 for Grass&Alfalfa, 0.379 for Alfalfa, and -0.030 for Grass in the case of fAPAR. For normal years, the correlations are 0.331 for Grass&Alfalfa, 0.407 for Alfalfa, and 0.399 for Grass in the case of fCover, and 0.165 for Grass&Alfalfa, 0.353 for Alfalfa, and 0.207 for Grass in the case of fAPAR.

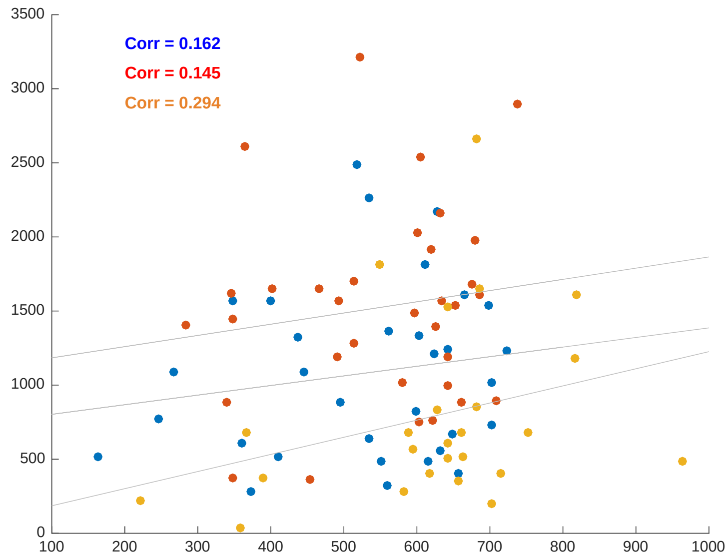


(a) Airbus fCover GPI scatterplot of exceptionally low yields in Saskatchewan, which are defined as the years with the GPI values lower than the 10% quantile.

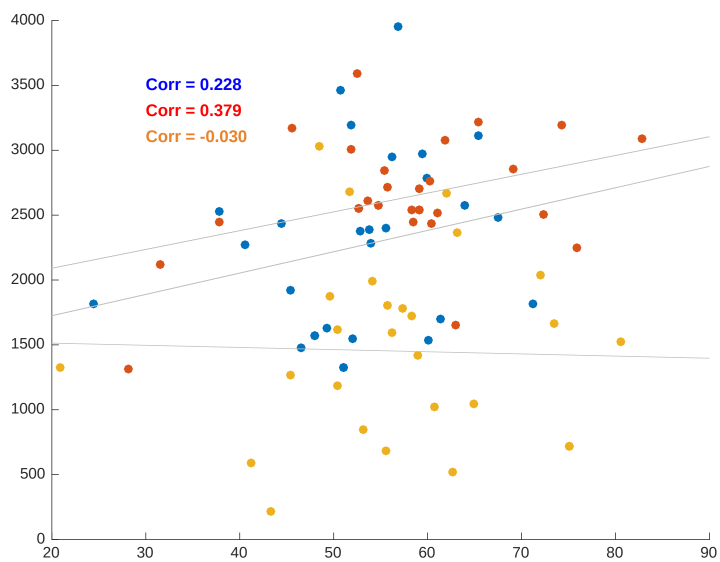


(b) Airbus fAPAR GPI scatterplot of exceptionally low yields in Saskatchewan, which are defined as the years with the GPI values lower than the 10% quantile.

Figure 7.25: Scatter plot of bad years. The figures show scatterplots of exceptionally low yields based on scenario analysis in Saskatchewan. The first figure shows the Airbus fCover GPI, and the second figure shows the Airbus fAPAR GPI. Blue, red, and orange dots represent the species of Grass&Alfalfa, Alfalfa, and Grass, respectively.

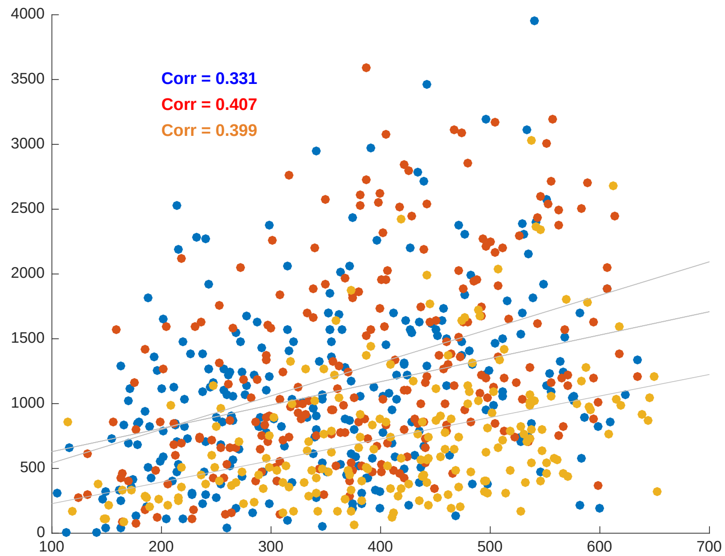


(a) Airbus fCover GPI scatterplot of exceptionally high yields in Saskatchewan, which are defied as the years with the GPI values higher than the 90% quantile.

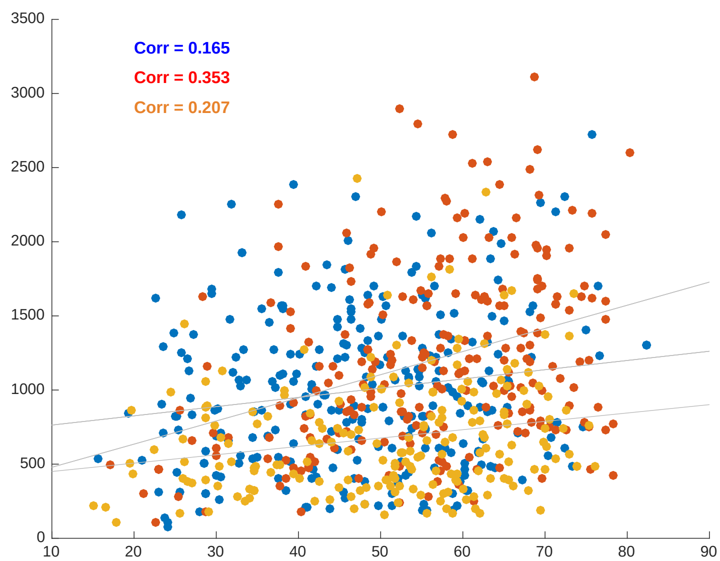


(b) Airbus fAPAR GPI scatterplot of exceptionally high yields in Saskatchewan, which are defied as the years with the GPI values higher than the 90% quantile.

Figure 7.26: Scatter plot of good years. The figures show scatterplots of the exceptionally high forage yields based on scenario analysis in Saskatchewan. The first figure shows the Airbus fCover GPI, and the second figure shows the Airbus fAPAR GPI. Blue, red, and orange dots represent species of Grass&Alfalfa, Alfalfa, and Grass, respectively.



(a) Airbus fCover GPI scatterplot of normal forage yields in Saskatchewan.



(b) Airbus fAPAR GPI scatterplot of normal forage yields in Saskatchewan.

Figure 7.27: Scatter plot of normal years. The figures show scatterplots of the normal forage yields based on scenario analysis in Saskatchewan. The first figure shows the Airbus fCover GPI, and the second figure shows the Airbus fAPAR GPI. Blue, red, and orange dots represent species of Grass&Alfalfa, Alfalfa, and Grass, respectively.

7.4. Analysis of Alternative FPI's

In this subsection, sixteen alternative Forage Production Indices (FPI's) are considered, including eleven vegetation indices, two biophysical parameter indices, and three indices based on weather station data.

7.4.1. Overview

7.4.1.1. Review of Alternative FPI's

Sixteen FPI's were computed as described in Section 6, and below they are briefly summarized.

FPI_1: NDVI AVHRR 1 km

FPI_2: NDVI MODIS 500 m - Daily Observation

FPI_3: NDVI MODIS 250 m - 8 Day Observation

FPI_4: GNDVI MODIS 500 m - Daily Observation

FPI_5: GNDVI MODIS 250 m - 8 Day Observation

FPI_6: EVI MODIS 500 m - Daily Observation

FPI_7: EVI MODIS 250 m - 8 Day Observation

FPI_8: MSAVI2 MODIS 500 m - Daily Observation

FPI_9: MSAVI2 MODIS 250 m - 8 Day Observation

FPI_{10}: OSAVI MODIS 500 m - Daily Observation

FPI_{11}: OSAVI MODIS 250 m - 8 Day Observation

FPI_{12}: LAI MODIS 500 m - Daily Observation

FPI_{13}: FPAR MODIS 500 m - Daily Observation

FPI_{14}: Accumulated Precipitation Weather Station

FPI_{15}: Heating Degree Days Weather Station

FPI_{16}: Cooling Degree Days Weather Station

7.4.2. Start and End Dates for the FPI's

For the validation of the various FPI's to the ground truth forage yield data, an important consideration is the start and end dates that correspond to the measurement values. In the province of Alberta, the measurement periods are roughly known based on the recorded values at the various test sites. It is assumed that the season start date is May 15, and the end dates correspond to the two measurement periods, which are either June 30 or August 15th.

In Saskatchewan, the ground truth forage yield data corresponds to the data recorded for the Tame-Hay insurance program. The end dates (or the measurement periods) are not known as only total yields are reported to SCIC. Therefore, a season start date of May 15th is assumed, which is consistent with Alberta. However, season end dates of July 31, August 31, and September 30 are empirically tested using correlation analysis. As an example, Figure 7.28 displays the average MSAVI2 time series values across all test sites in Saskatchewan for Alfalfa in 2002 shown by the blue line, and where the grey shaded band around the blue line represents the 95th percentile of the MSAVI2 values. This example shows how the average MSAVI2 values change throughout the season based on a season start date of May 15 (Julian day 135) and various season end dates, including July 31 (Julian day 212), August 31 (Julian day 243) and September 31 (Julian day 272). In this example, it shows that alfalfa in 2002 had peak growth around June 30 (Julian day 181), followed by a decline, and moderate regrowth beginning around August 8 (Julian day 220). Figure 7.29 shows the time series of MASVI2 for each test in Saskatchewan for Alfalfa in 2002. The various coloured lines represent the MASVI2 time series at each test site, and shows the variation across the locations in the province.

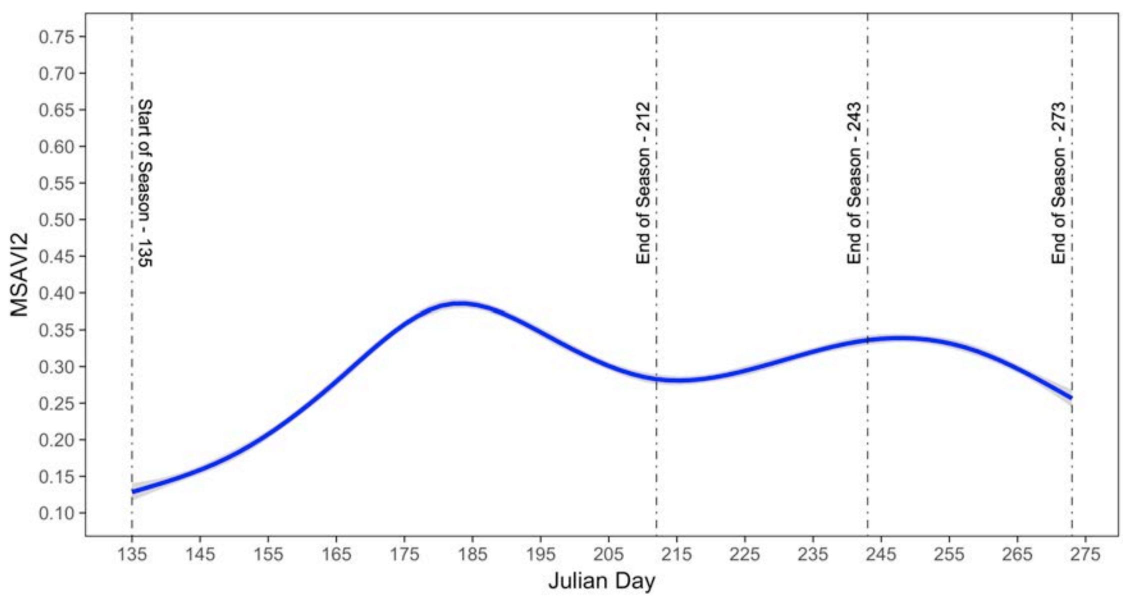


Figure 7.28: Average MSAVI2 time series values across all test sites in Saskatchewan for Alfalfa in 2002 shown by the blue line (and the grey band represents the 95th percentile of the MSAVI2 values).

As a comparison, Figure 7.30 displays the average MSAVI2 time series values across all test sites in Saskatchewan for Alfalfa in 2004 shown by the blue line, and where the

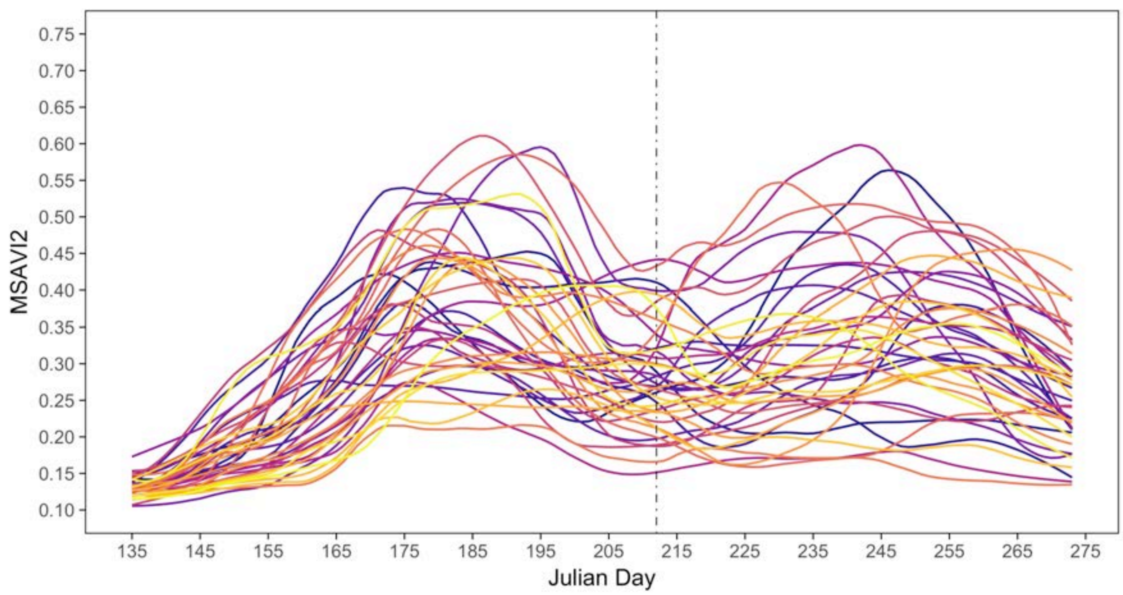


Figure 7.29: MSAVI2 time series values in Saskatchewan for Alfalfa in 2002 shown by the various coloured lines for each test site.

grey shaded band around the blue line represents the 95th percentile of the MSAVI2 values. This example shows how the average MSAVI2 values change throughout the season based on a season start date of May 15 (Julian day 135) and various season end dates, including July 31 (Julian day 212), August 31 (Julian day 243) and September 31 (Julian day 272). In this example, it shows that alfalfa in 2004 had peak growth around July 14 (Julian day 195), followed by a continuous decline until season end (i.e. no regrowth). This is in contrast to the 2002 example above, where regrowth was observed. Figure 7.31 shows the time series of MASVI2 for each test in Saskatchewan for Alfalfa in 2004. The various coloured lines represent the MASVI2 time series at each test site, and shows the variation across the locations in the province.

Based on empirical analysis, an end date of July 31 is shown to have the strongest relationship to the ground truth data on average. However, assumptions using the other season end dates, including August 31, and September 30, are quite similar. The next stage of the research will focus on obtaining more site specific information to better quantify the growth cycle and yield measurements corresponding to specific measurement dates.

7.4.3. Satellite-Based FPI's Validation Analysis

In this subsection, several vegetation indices and biophysical indices considered in this report are described, and the results are analyzed. The vegetation indices include 1) NDVI AVHRR 1 km (for Alberta only), 2) NDVI MODIS 500 m, 3) NDVI MODIS

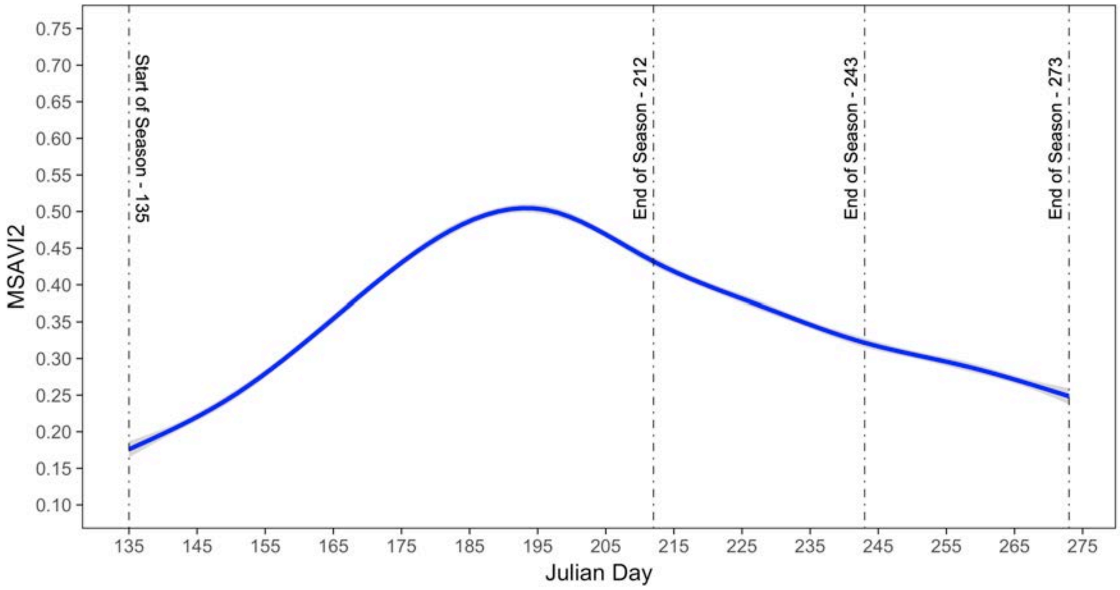


Figure 7.30: MSAVI2 time series values in Saskatchewan for Alfalfa in 2002 shown by the various coloured lines for each test site.

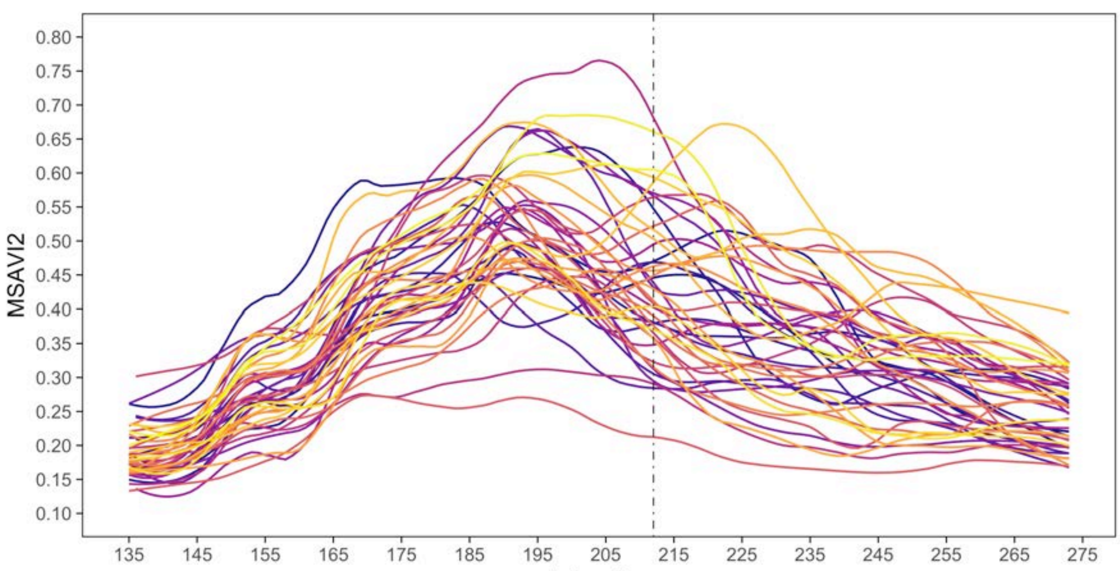


Figure 7.31: MSAVI2 time series values in Saskatchewan for Alfalfa in 2002 shown by the various coloured lines for each test site.

250 m, 4) GNDVI MODIS 500 m, 5) GNDVI MODIS 250 m 6) EVI MODIS 500 m, 7) EVI MODIS 250 m 8) MSAVI2 MODIS 500 m, 9) MSAVI2 MODIS 250 m, 10) OSAVI MODIS 500 m., 11) OSAVI MODIS 500 m, 12) OSAVI MODIS 250 m, 13) LAI MODIS 500 m, and 14) FPAR 500 m. A detailed time series for each of the indices is constructed over the period from 2002 to 2016 for Alberta, and 2002 to 2015 for Saskatchewan. The satellite-derived indices are then compared to the same ground truth forage yield data that was used to validate the two Airbus GPI's described previously in this section.

7.4.3.1. Alberta Comparison of Alternative FPI's

Table 7.9 provides a summary of the eleven vegetation FPI's considered in this study, while Table 7.10 provides a summary of the two biophysical parameter FPI's considered. For each of the alternative FPI's, the average correlation results over the period 2002 to 2016 are shown for the measurement periods of August and June & August combined for both native and improved pastures combined. The results show that overall the correlations from May 15 to August 15th are strongest. Further, the table shows that OSAVI MODIS 500 m - Daily has the highest average correlation results of 61.5% in August, closely followed by NDVI MODIS 500 m - Daily with average correlation results of 61.4%. This is compared to GNDVI MODIS 500 m - Daily with average correlation of 60.5%, MSAVI2 MODIS 500 m - Daily of 60.4%, and 60.03% for EVI MODIS 500 m - Daily. The MODIS 250 m - 8 Day indices have comparatively lower correlations.

In addition to the average correlation results across all of the sample years, it is interesting to explore the year-by-year correlations for some of the important FPI's, as examples. Table 7.11 provides the results for OSAVI MODIS 500 m - daily, NDVI MODIS 250 m - 8 day, and FPAR MODIS 500 m - daily for comparison over each of the years from 2002 to 2016 for the August measurement period (May 15 and end date of August 15). It is interesting to see that the correlations are fairly stable over the years, with the exception of the year 2003 and 2008. However, it should be noted that the lower correlations in 2003 and 2008 are consistent across all of the GPI's and FPI's considered in this research, and this could be due to several of the data limitations previously discussed, such as timing of the measurement period, representativeness of the sample, etc. Overall, the results show that FAPAR produces the highest average correlation, with values as high as 86.0%.

7.4.3.2. Saskatchewan Comparison of Alternative FPI's

Table 7.12 provides a summary of the eleven vegetation FPI's considered in this study, while Table 7.13 provides a summary of the two biophysical parameter FPI's considered. For each of the alternative FPI's, the average correlation results over the period 2002 to 2015 are shown for the measurement periods of May 15 - July 31, May 15 - August 31, and May 15 - September 30 for three types of forage, including Grass, Alfalfa and

Table 7.9: Results of the Vegetation Indices Forage Yield Correlation Analysis in Alberta, with average values reported for the years 2002 to 2016.

Alternative Forage Production Indices (FPI's)	**Measurement Period**	**Average Correlation**
NDVI MODIS 500 m - Daily	Aug	0.613
	Jun & Aug	0.542
NDVI MODIS 250 m - 8 Day	Aug	0.567
	Jun & Aug	0.528
GNDVI MODIS 500 m - Daily	Aug	0.605
	Jun & Aug	0.494
GNDVI MODIS 250 m - 8 Day	Aug	0.564
	Jun & Aug	0.489
EVI MODIS 500 m - Daily	Aug	0.603
	Jun & Aug	0.569
EVI MODIS 250 m - 8 Day	Aug	0.438
	Jun & Aug	0.456
MSAVI2 MODIS 500 m - Daily	Aug	0.604
	Jun & Aug	0.581
MSAVI2 MODIS 250 m - 8 Day	Aug	0.543
	Jun & Aug	0.552
OSAVI MODIS 500 m - Daily	Aug	0.615
	Jun & Aug	0.556
OSAVI MODIS 250 m - 8 Day	Aug	0.559
	Jun & Aug	0.536

Note: June is defined as the measurement period with a season start date of May 15 and end date of June 30, and Aug is defined as the measurement period with a season start date of May 15 and end date of August 15.

Table 7.10: Results of the Biophysical Parameter Forage Yield Correlation Analysis in Alberta, with average values reported for the years 2002 to 2016.

Alternative Forage Production Indices (FPI's)	**Measurement Period**	**Average Correlation**
FAPAR MODIS 500 m - Daily	Aug	0.620
	Jun & Aug	0.581
LAI MODIS 250 m - 8 Day	Aug	0.597
	Jun & Aug	0.612

Note: Jun is defined as the measurement period with a season start date of May 15 and end date of June 30, and Aug is defined as the measurement period with a season start date of May 15 and end date of August 15.

Table 7.11: Select Results for the Forage Yield Correlation Analysis in Alberta for the years 2002 to 2016 for the August measurement period (May 15 and end date of August 15).

Year	**OSAVI MODIS 500 m - daily**	**NDVI MODIS 250 m - 8 day**	**FAPAR MODIS 500 m - daily**
2002	0.694	0.699	0.708
2003	0.078	0.120	0.156
2004	0.555	0.420	0.577
2005	0.713	0.750	0.744
2006	0.641	0.630	0.640
2007	0.614	0.548	0.604
2008	0.421	0.418	0.404
2009	0.578	0.575	0.589
2010	0.616	0.512	0.645
2011	0.509	0.317	0.532
2012	0.729	0.674	0.706
2013	0.650	0.519	0.633
2014	0.701	0.651	0.650
2015	0.858	0.797	0.847
2016	0.864	0.872	0.860
average	0.615	0.567	0.620

Note: OSAVI 500 m values are calculated using the MODIS MCD43A4 data product, NDVI 250 m values are calculated using the MODIS MOD09A1 data product, and the FAPAR 500 m values are obtained from the MODIS MCD15A2H data product.

Grass/Alfalfa. The results show that MSAVI2 has the strongest average correlations over the sample period relative to the other indices. Further, the measurement period from May 15 - July 31 for Alfalfa has the strongest correlation.

Based on the results of the overall correlations, the year-by-year correlations are also examined for select FPI's, including NDVI MODIS 500 m - Daily Observations, MSAVI2 MODIS 500 m - Daily Observations, and LAI MODIS 500 m - Daily Observations, which are shown in Table 7.14. These three FPI's are selected because NDVI serves as an interesting benchmark given the prevalence of this vegetation index in literature and several operational forage index-based insurance plans around the world. MSAVI2 is selected because it was the best performing index based on the summary results presented in Table 7.12 and Table 7.13. Finally, LAI is selected because it was the best performing biophysical parameter index based on the overall average correlations.

The results show that NDVI MODIS 500 m - Daily produces correlations that are overall weaker compared to MSAVI2 and LAI. In addition, there are two years, 2003 and 2012 where correlations are negative. Excluding the negative correlations, the NDVI correlations can be as low as 0.015 in 2011 and as high as 0.608 in 2015. MSAVI 2 on the other hand appears to have more stable results. The lowest correlation is reported in 2010 at 0.068, and the highest is in 2013 at 0.792. In comparison, LAI has results that are lower than MSAVI2, but, higher than NDVI. The lowest correlation for LAI is 0.090 in 2010 and the highest is 0.702 in 2007.

7.4.4. Weather Station Index Analysis

In the analysis for the FPI's constructed from the ground weather station data in both Alberta and Saskatchewan that follows in this subsection, the Forage Rainfall Insurance Program (FRIP) in Saskatchewan is used as the motivation for the assumptions regarding the weighting of the variables in each month to construct the index. The FRIP is available for native and tame grazing acres, providing protection for pastureland in the event that seasonal precipitation is below the long-term average. The current FRIP contract provides producers with several alternatives regarding the weighting of accumulated precipitation (AccPcpn) by month during the growing season. This is intended to provide flexibility to best match the producer's own growing and management experience. The weighting assumptions used for the analysis in Alberta are shown in Table 7.15, and the weighting assumptions used for the analysis in Saskatchewan are shown in Table 7.16. Therefore, in this subsection three weather station FPI's are considered, including HDD, CDD and AccPcpn. Further, for each weather station FPI, three weighting alternatives are considered using the current FRIP contract specifications as a guideline.

Table 7.17 shows the correlation results for Alberta over the sample from 2006 to 2016. The results show that the highest correlation is with the precipitation variable for the second weighting option (Pcpn02) of 0.1251. To examine to robustness of the

Table 7.12: Results of the Vegetation Indices Forage Yield Correlation Analysis for Saskatchewan, averaged over the years 2002 to 2015.

Alternative Forage Production Indices (FPI's)	**Measurement Period**	**Average Correlations 2002 - 2015**		
	(Start Date - End Date)	Grass	Alfalfa	G/A*
NDVI MODIS 500 m - Daily	May 15 - July 31	0.231	0.245	0.204
	May 15 - August 30	0.208	0.268	0.221
	May 15 - September 30	0.191	0.231	0.210
NDVI MODIS 250 m - 8 Day	May 15 - July 31	0.212	0.359	0.290
	May 15 - August 30	0.181	0.351	0.278
	May 15 - September 30	0.173	0.309	0.272
GNDVI MODIS 500 m - Daily	May 15 - July 31	0.229	0.241	0.197
	May 15 - August 30	0.214	0.270	0.221
	May 15 - September 30	0.198	0.245	0.216
GNDVI MODIS 250 m - 8 Day	May 15 - July 31	0.187	0.330	0.205
	May 15 - August 30	0.170	0.334	0.222
	May 15 - September 30	0.170	0.287	0.223
EVI MODIS 500 m - Daily	May 15 - July 31	0.466	0.518	0.373
	May 15 - August 30	0.402	0.491	0.349
	May 15 - September 30	0.378	0.434	0.330
EVI MODIS 250 m - 8 Day	May 15 - July 31	0.340	0.486	0.411
	May 15 - August 30	0.307	0.482	0.370
	May 15 - September 30	0.309	0.447	0.368
MSAVI2 MODIS 500 m - Daily	May 15 - July 31	0.469	0.555	0.366
	May 15 - August 30	0.401	0.527	0.338
	May 15 - September 30	0.379	0.471	0.330
MSAVI2 MODIS 250 m - 8 Day	May 15 - July 31	0.325	0.501	0.357
	May 15 - August 30	0.284	0.470	0.344
	May 15 - September 30	0.269	0.429	0.339
OSAVI MODIS 500 m - Daily	May 15 - July 31	0.385	0.461	0.332
	May 15 - August 30	0.326	0.440	0.303
	May 15 - September 30	0.311	0.387	0.293
OSAVI MODIS 500 m - Daily	May 15 - July 31	0.267	0.430	0.323
	May 15 - August 30	0.229	0.409	0.310
	May 15 - September 30	0.216	0.366	0.304

Note: G/A* denotes Grass & Alfalfa.

Table 7.13: Results of the Biophysical Parameter Forage Yield Correlation Analysis for Saskatchewan, averaged over the years 2002 to 2015.

Alternative Forage Production Indices (FPI's)	**Measurement Period**	**Average Correlations 2002 - 2015**		
	(Start Date - End Date)	Grass	Alfalfa	A/G*
LAI MODIS 500 m - 8 Day	May 15 - July 31	0.275	0.386	0.337
	May 15 - August 30	0.256	0.383	0.322
	May 15 - September 30	0.257	0.347	0.325
FPAR MODIS 500 m - 8 Day	May 15 - July 31	0.265	0.352	0.323
	May 15 - August 30	0.225	0.362	0.303
	May 15 - September 30	0.228	0.343	0.304

Note: A/G* denotes Alfalfa & Grass.

Table 7.14: Average Correlations for Alternative Forage Production Indices (FPI's) for Assumed Measurement Period May 15 - July 31 for Saskatchewan.

Type	Year	NDVI MODIS 500 m - Daily	MSAVI2 MODIS 500 m - Daily	LAI MODIS 500 m - 8 Day
Alfalfa	2002	0.462	0.718	0.712
Alfalfa	2003	-0.223	0.457	0.290
Alfalfa	2004	0.396	0.614	0.478
Alfalfa	2005	0.381	0.764	0.642
Alfalfa	2006	0.163	0.552	0.256
Alfalfa	2007	0.325	0.733	0.702
Alfalfa	2008	0.487	0.726	0.672
Alfalfa	2009	0.323	0.513	0.266
Alfalfa	2010	0.105	0.068	0.090
Alfalfa	2011	0.015	0.404	0.088
Alfalfa	2012	-0.149	0.239	0.086
Alfalfa	2013	0.390	0.792	0.634
Alfalfa	2014	0.149	0.501	0.130
Alfalfa	2015	0.608	0.686	0.361

Table 7.15: Monthly Precipitation Weighting Alternatives Assumed for the Alberta Weather Station Analysis

Monthly Weather Weighting Alternatives									
	June Cut				August Cut				
	April	May	June	Total	April	May	June	July	Total
Option 1	1/3	1/3	1/3	100%	30%	30%	30%	10%	100%
Option 2	1/3	1/3	1/3	100%	10%	40%	40%	10%	100%
Option 3	1/7	3/7	3/7	100%	10%	30%	30%	30%	100%

Table 7.16: Monthly Precipitation Weighting Alternatives Assumed for the Saskatchewan Weather Station Analysis

Monthly Weather Weighting Alternatives					
	April	May	June	July	Total
Option 1	30%	30%	30%	10%	100%
Option 2	10%	40%	40%	10%	100%
Option 3	10%	30%	30%	30%	100%

correlations, the correlations are also examined (but not included in this report due to space constraints). Overall, however, the year-by-year analysis shows a great deal of variation indicating that the FPI's based on the ground weather station data is not very robust. This variation may present a concern when used solely to construct the underlying insurance index, compared to some of the GPI's or FPI's that appear to be more stable.

Table 7.17: Correlation Matrix of the Ground Truth Yield and Weather Variables for Alberta. Results correspond to correlations over the sample period from 2006-2016.

	Yield	PcpnO1	HDDO1	CDDO1	PcpnO2	HDDO2	CDDO2	PcpnO3	HDDO3	CDDO3
Yield	1.0000									
PcpnO1	0.1007	1.0000								
HDDO1	-0.0274	0.7533	1.0000							
CDDO1	-0.1067	0.2682	0.4692	1.0000						
PcpnO2	0.1251	0.9931	0.7424	0.2875	1.0000					
HDDO2	-0.0666	0.7329	0.9780	0.3849	0.7048	1.0000				
CDDO2	-0.0981	0.2555	0.4472	0.9943	0.2787	0.3534	1.0000			
PcpnO3	0.0831	0.9891	0.7614	0.2559	0.9803	0.7455	0.2466	1.0000		
HDDO3	-0.0628	0.7446	0.9813	0.3899	0.7187	0.9963	0.3610	0.7574	1.0000	
CDDO3	-0.0400	0.2739	0.4208	0.9489	0.3049	0.3074	0.9455	0.2414	0.3142	1.0000

Table 7.18 shows the correlation results for Saskatchewan over the sample from 2006 to 2015. The results show that the highest correlation is with the precipitation variable for the second weighting option (Pcpn02) of 0.2312. To examine to robustness of the correlations, the correlations are also examined (but not included in this report due to space constraints). Overall, however, the year-by-year analysis shows a great deal

of variation indicating that the FPI's based on the ground weather station data is not very robust.

Table 7.18: Correlation Matrix of the Ground Truth Yield and Weather Variables for SK. Results correspond to correlation for a sample period of 2006-2015.

	Yield	PcpnO1	HDDO1	CDDO1	PcpnO2	HDDO2	CDDO2	PcpnO3	HDDO3	CDDO3
Yield	1.0000									
PepnO1	0.2042	1.0000								
HDDO1	-0.0409	0.1005	1.0000							
CDDO1	0.0645	-0.0686	-0.7317	1.0000						
PepnO2	0.2312	0.9701	0.0120	-0.0108	1.0000					
HDDO2	-0.0779	0.1129	0.9087	-0.7947	0.0198	1.0000				
CDDO2	0.0550	-0.0779	-0.7489	0.9969	-0.0219	-0.8013	1.0000			
PepnO3	0.1913	0.9303	0.2333	-0.2160	0.9156	0.2319	-0.2177	1.0000		
HDDO3	-0.0735	0.0619	0.9267	-0.8149	-0.0262	0.9888	-0.8193	0.1984	1.0000	
HDDO3	0.0897	-0.0388	-0.6530	0.9715	0.0226	-0.7449	0.9496	-0.2031	-0.7712	1.0000

SECTION 8

Summary

This section provides a summary of the main findings from phase one of the research. The overall objective was to develop improved index-based forage insurance products for the Provinces of Alberta and Saskatchewan, to address the current low demand for forage insurance and improve producer risk management. A main focus of this first phase of the research was on the preliminary feasibility assessment and development of index-based forage insurance using satellite-derived indices. The data used to construct the indices included two proprietary Grass Production Indices (GPI's) based on biophysical parameters developed by Airbus Defence & Space, and sixteen alternative Forage Production Indices (FPI's) based on vegetation and biophysical parameter approaches, as well as ground weather station observations, computed from publicly available data. To validate the GPI's and FPI's, ground truth forage yield data is used. In Alberta, this corresponded to improved and native pasture clip sites, and for Saskatchewan this corresponded to tame-hay yield data, which included alfalfa, grass and alfalfa/grass mix.

The results in this phase of the research should be interpreted with caution, and importantly the correlations should be considered in terms of their relative performance to one another (rather than the value itself, or compared to results of other studies, which have made other assumptions regarding data aggregation, processing assumptions, etc.). A number of ground truth yield data limitations were noted in this phase of the research, largely stemming from possible concerns over representativeness of samples, precise measurement dates and locations of the samples, among other concerns documented throughout the report. The results show that there are strong correlations in the satellite-based indices compared to the ground truth forage yield data in both Alberta and Saskatchewan. This is compared to the indices constructed from ground weather station variables, which show overall weaker relationships with the yield data in both provinces.

Overall the results for Alberta (Saskatchewan) showed that the Airbus fCover GPI, Airbus FAPAR GPI, OSVI alternative FPI, MSAVI2 alternative FPI, and FPAR alternative FPI had the strongest correlations with the ground truth data. When considering the average results over the entire sample period, the correlations were 68.99% (48.55%), 69.16% (34.33%), 61.5% (46.10%), 60.4% (55.50%), and 62.0% (36.20%), respectively. When considering the correlations for individual years, the results could be as high as 86.4% in 2016 for OSAVI in Alberta, and 79.2% for MSAVI2 in Saskatchewan, as examples. Comparatively, the FPI's constructed from the ground weather station observations, including accumulated precipitation (Precpn), heating degree days (HDD), and cooling degree days (CDD), along with three weighting options to weight the variables across the various months, showed much lower correlations. In both provinces, precipitation showed the highest overall correlation with the ground truth data, which was 12.51% in Alberta and 23.12% in Saskatchewan. It is important to note that the year-to-year variability of the correlations for the weather station-derived FPI's are not stable and could change considerably from one year to the next.

A main focus of phase two of the research should be on selecting the best performing indices in phase one, and proceeding with further refinement of the model, the design and testing of the insurance product, pricing and actuarial risk assessment, and validation with producers. To accomplish this, the following have been identified as key priorities of the next phase of research. First, it is recommended that more comprehensive ground truth forage yield data is obtained. This includes more detailed information pertaining to measurement dates, and locations, among other considerations. Further, the current analysis focused only on pasture in Alberta and tame-hay in Saskatchewan, therefore, the analysis should be extended to consider tame-hay in Alberta, and pasture in Saskatchewan. To accomplish this, it is recommended that the researchers obtain additional historical data from AFSC and SCIC, as well as other existing forage databases. Further, it is recommended that at least 10 producers from each province are selected and ground-truthing representative of the farm is conducted over at least two growing seasons to aide in designing and validating the forage insurance products. Phase two of the research should also focus on the integration of high-resolution satellite imagery data to augment the medium-resolution satellite imagery data, which was the focus of the current study. In addition, it is recommended that hybrid indices are explored and empirically investigated to study the possible improvement of combining various vegetation and biophysical parameter indices, and ground weather station observations, using advanced statistical approaches, such as machine learning. The unit area of insurance should also be studied to better understand the desired scale of the underlying insurance index from both the perspectives of producers as well as the government crop insurance companies. Finally, phase two of the research should focus on validation of the final insurance product in terms of basis risk, which measures the error in the indemnity computed from the insurance index relative to the actual loss experienced on the farm.

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