Approaches to Atmospheric Modelling and Multi-source Data Collection and Processing for the FINCH CubeSat

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Abstract

We are presenting an atmospheric modelling and inversion model for the FINCH (Field Imaging Nanosatellite for Crop residue Hyperspectral mapping) pushbroom hyperspectral imaging CubeSat, built by the University of Toronto Aerospace Team Space Systems division. Such a model will allow us to validate our spectral unmixing pipeline under possible FINCH imaging conditions, as well as finalise and validate the atmospheric inversion pipeline for FINCH-sourced data, thus permitting scientifically useful data collection. FINCH, through innovations in crop residue cover mapping, will further enable sustainable agricultural practices, and serve as a template for other low cost, mission focused, scientificality useful remote sensing missions. We have accounted for all significant aspects that impact our capability to map crop residue cover, and we have developed a process to simulate data for training and validation.

1. Introduction

The University of Toronto Aerospace Team’s Space Systems division is an entirely student led engineering design team that develops highly specialised small satellites with a relatively low budget. We are currently designing FINCH - the Field Imaging Nanosatellite for Crop Residue Hyperspectral Mapping, a 3U satellite with a hyperspectral sensor for mapping crop residue cover. Crop residue is critical to agricultural practices and crop residue coverage of a field is a vital metric for farmers to properly account for its effect. Non Photosynthetic Vegetation (NPV) retards soil erosion, traps moisture, and is a source of nutrients; it can conversely also cause a lack of sun exposure and prevent proper seeding and growing later on. (Dennison et al., 2023, Pepe et al., 2020) Therefore accurate estimation of crop residue abundance is an important consideration for sustainable farming, and thus far there are three primary methods of doing this: manual estimation by individuals on-site, aerial based remote sensing missions, and space based remote sensing missions. On-site estimation, though accurate, is (for a large scale survey and data quantities) time consuming on a large scale, not generalizable, and impractical under less than ideal conditions (remote locations, inclement weather, shortage of trained individuals). Aerial based remote sensing missions exist for this purpose in two main types, fixed wing and UAV. Fixed wing missions, while effective, are prohibitively expensive when not externally funded. UAV missions have many of the same issues as manual estimation, as they require a qualified on-site pilot, and the flights are generally very short and isolated to small sections of the fields, which make them both expensive and impractical, not least due to specific weather requirements. Alternatively, satellite missions are expensive at first, however have very low operating costs once in orbit, and can be used to cover multiple farms with relative frequency, depending on the orbit they can also image farms at frequencies that are prohibitively impractical with any other method. (Dennison et al., 2023, Dennison et al., 2019, Pepe et al., 2020) Though field survey techniques have historically been used to estimate crop residue cover; however, they are labor intensive and time consuming. Therefore remote sensing methods, using airborne/UAV or satellite sensors, have been developed for improving efficiency and accuracy of crop residue mapping (Dennison et al., 2023, Dennison et al., 2019, Pepe et al., 2020). These primarily depend on a key spectral feature sensitive to crop residue that is the lignin-cellulose, which can be exploited via spectral indices or through spectral unmixing, however requires highly expensive and resource intensive sensors. This is unfortunately beyond the engineering capability of FINCH, and alternative methods have been explored that require highly accurate atmospheric modells. (Armstrong et al., 2025) Hyperspectral satellite remote sensing is far from a new field and clear alternatives that are already capable of fulfilling our scientific requirements are missions such as EnMap, Landsat, and Worldview3. Although these satellites can be, and have been used to analyze crop residue, the missions themselves were not specifically designed for crop residue mapping, and thus have a few inherent holes in their use that we aim to fill. We plan to provide more affordable and convenient alternatives that enables the agricultural industry to map crop residue abundances more efficiently. Though FINCH is not designed to operate longer than a year, the development of FINCH-like missions should not exceed CAD 700,000 including launch, with each of these alternatives costing hundreds of millions per launch. Therefore, as far as crop residue is concerned, accurate cover maps on large scales can be produced for a fraction of the cost of launching a dedicated crop residue mapping mission using the lignin-cellulose absorption band, even with a large constellation of FINCH-like missions. These missions, while fully capable of mapping crop residue, can also be impractical for use in agriculture as they may not have ideal temporal resolution over the imaging sites, and are extremely expensive on an image by image basis when compared to a dedicated cubesat that is theoretically capable of imaging multiple farms, with orbital requirements set by this mission and capable of reliably mapping crop residue at the times that such data is needed.

Therefore, a gap remains in satellite remote sensing platforms and technologies that can be utilized to practice sustainable agriculture at the farm scale. The FINCH mission seeks to fill this gap by developing a technological demonstration of a low-cost satellite platform for operational crop residue mapping. The engineering challenges in designing such a system with a low budget are substantial. Weight, volume, thermal and power budgets for a 3U satellite make it difficult to use a hyperspectral sensor covering the 2100 nm spectral range. Mass and volume constraints also inhibit the payload's ability to achieve high spatial resolution. These constraints limit our design options for spectral and spatial resolution to between 900-1700 nm and between 90 - 150 m respectively. Consequently there is a gap between scientific requirements and feasible engineering implementations. To bridge this gap, a designated remote sensing team was founded whose purpose is to develop a rigorous method of validating design decisions and to assess prospected crop residue mapping results. This Science team is in part responsible for the implementation of atmospheric and surface modelling procedures to facilitate acquisition of usable data as well as correct for, and standardize factors that would impact the results of unmixing.

Any effort involving top of atmosphere Short-Wave Infrared (SWIR) data must take careful account of the effects of atmospheric absorption on large swaths of the spectrum which otherwise would prove to be a significant noise source for any processing that fails to account for it. A pipeline has been developed using standard off the shelf radiative transfer models and mission specific data, that will allow us to train unmixing algorithms on accurate spectra and invert atmospheric effects on FINCH data. As it stands, little research has been conducted into the use of this band for its utility in agricultural remote sensing given its suboptimal properties in both atmospheric absorption, the spectral characteristics of soil and vegetation, and the prevalence of alternative options. Therefore, much of the work being done for FINCH, while relatively standard is, to a degree untried, and a good deal of the work being done for this project is new.

FINCH has been, for the past few years, an entirely student-led mission aimed at launching a 3U CubeSat to demonstrate the practicality, capability, and cost effectiveness of small-scale inexpensive remote sensing satellites to map crop residue abundances as an alternative to the existing solutions. Unfortunately both the form factor and Engineering requirements have limited the capabilities of the design, necessitating highly accurate atmospheric, surface, and space environment models in order to return reasonable data. When developing this, unfortunately timeline constraints did not permit either the atmospheric model or the unmixing algorithm to be developed prior to one another, therefore few hard requirements could be set prior to their mutual development. However in spite of this, the unmixing team was capable of providing tentative requirements for data quality, and bands of interest. This allowed for sufficient guidance in preparing the atmospheric model, and in determining the necessary conditions for the pipeline as a whole.

Without a full atmospheric radiative transfer pipeline, approaches to unmixing would be significantly hindered by unreasonably high noise in the bands we intend to perform unmixing on. This would almost certainly make any spectral unmixing attempt a practical impossibility. However, with an atmospheric pipeline, we would be able to account for the vast majority of atmospheric effects from bands of interest to us, and train our unmixing algorithms on Top of Atmosphere (TOA) propagated data and Top of Canopy (TOC) data. This will be validated using our unmixing algorithms on propagated and unpropagated data, and will aid in determining the sensitivity of the algorithms.

With the requirement for a comprehensive pipeline, site specific models must be developed and used alongside standard methods particularly for the Bi-directional Reflectance Distribution Functions (BRDF), surface albedo, and atmospheric composition. Unfortunately, few common BRDFs can be used for FINCH data, given their unsuitability to this particular medium and the wide range of types of possible farm field. Therefore it is necessary to develop one and properly implement it within our radiative transfer models. This is based largely on ground truth data, as well as general soil properties with regard to the effect of tillage on the diurnal and view angular reflectance. To properly model atmospheric effects, the DART (Discrete anisotropic radiative transfer) model is being used as our primary radiative transfer model for both TOA and Bottom of Atmosphere (BOA) corrections. Settings used to create both an atmospheric model and an earth scene or standardized after separate development for each component. We have also previously used MODTRAN, for transmittance modelling in data propagation and inversion.

We must also contend with non-standard atmospheric compositions as well as increased sensitivity to common atmospheric components. Chief among these are farm-specific gases, aerosols, and compounds; particularly pesticides, products of fertilizer off gassing, as well as other organic and synthetic materials. We also need to account for a more erratic ozone absorption band as well as the effect of artificially produced gases and aerosols in low concentration. These have varying effects across our band, and can pose issues that would affect the validity of unmixing results given the expected sensitivity of the algorithm. Our aim is to stress test unmixing algorithms by unmixing spectra with various simulated atmospheric conditions to ensure FINCH's data can be analyzed within pre-defined accuracy expectations.

Each element of the pipeline must be strenuously tested using both real and generated data, to determine effectiveness and reliability across expected conditions. To facilitate this, as well as to accommodate testing of unmixing algorithms, the pipeline is automated in Python, and combines commercially available and open source software with our own methods and models. This is all contingent on a large quantity of both TOC and TOA data being collected from multiple sources as well as generated through the use of accurate models. Atmospheric correction across our spectral range can also result in the data from FINCH finding use outside of this specific use case, and expands the capability of the satellite.

2. Background

2.1 Data Collection and Preparation

Collecting data for this paper involved a multisource approach, using both pure endmember Spectra collected at labs and TOA data from the ENMAP satellite. (Armstrong, et al., 2025) For the purposes of validating our atmospheric models, pure endmembers were combined with various mixed abundance spectra, which were then propagated through the atmosphere accounting for various expected conditions. This was then inverted to BOA, and compared with ENMAP sourced data to create a baseline inverted dataset that could be used in conjunction with ENMAP data for validation.

In this paper we are using statistical models that are best suited for use in describing correlation or accuracy to compare spectra, and determine effect. The decision behind this is based on the utility of these processes in comparing the shape of theSpectra with one another, discounting their comparative magnitude, and only looking at differences in shape.

2.2 DART Radiative Transfer Model

The use of DART for this project was decided on after a comprehensive review of available radiative transfer models, and was integrated into general use at UTAT Space Systems where applicable, shortly after its acquisition in the winter of 2025. Since then it has become our primary radiative transfer model for both the analysis of what measures should be taken to strengthen the atmospheric conversion pipeline, and for creating atmospherically propagated data. Using this model we are able to simulate ground, vegetation, atmosphere, and top of atmosphere effects. In the model we are also able to create a simulation of the FINCH optical system FINCH-EYE, based on the current design of the system. (Shofman et al., 2025) Using this we are able to accurately model the effect of varying conditions on the direct irradiance at the sensor, and the effect of diffuse radiation on the Spectrum. (Philippe, 2021)

2.3 Implications for Unmixing

The rationale for having an atmospheric modeling pipeline to begin with, is based on determinations that have been made given the expected sensitivity of the unmixing algorithm, and the magnitude of the spectral characteristics that it relies on. While the algorithm may theoretically be capable of unmixing crop residue data given static atmospheric conditions, as shown here, there is significant variation in the absorption characteristics of the atmosphere and of the imaging conditions such that they must be counted for. If this is not done, then the abundance estimation returned by unmixing algorithms would be valueless. Early attempts at unmixing, with noise consistent or lower than variation expected from variations in imaging conditions have resulted in significantly reduced effectiveness, even when using trained deep learning algorithms, that prevented effective unmixing. (Augspach et al., 2026) as the unmixing algorithm has also not yet been finalized, it is necessary to account for all mitigating factors that can be effectively modeled within our capabilities, as any significant uncertainty in the reflectance spectrum returned by FINCH could potentially result in significantly higher uncertainties, than are necessary for useful data.

2.4 TOA Effects

As with any satellite remote sensing mission, we must account for diffuse atmospheric irradiance under multiple circumstances. DART fortunately has algorithms that model this, given specifications of the sensor itself, as well as its location and orientation. (Philippe, 2021) as can be seen in figures 1 and 2, this varies significantly depending on atmospheric composition and cloud cover, to the extent that if there is any significant layer of cumulus cloud, as in figure 2, the vast majority of at sensor irradiance is a result of atmospheric reflectance. However, as we can see in figure 3, so long as the cloud is not unreasonably large, it can theoretically be removed or otherwise accounted for.

As we can see in figure 4, the viewing angle of the satellite has a large impact on the extent of the absorption that takes place, however this is mostly concern for specific absorption bands which are increasing in magnitude as a result of this, rather than the very clear Water absorption bands, which are already near total or total. The VZA (Viewing Zenith Angle) is, unfortunately, a complex engineering requirement, based on the ability of the altitude determination and control system to point the satellite while accounting for Sun position relative to both the solar panels and photosensitive components. Therefore, instead of imposing scientific requirements on the VZA, we must be capable of accounting for a reasonable margin of values based on estimations provided by the ACDS team. Thus far, while most simulations have assumed nadir for Simplicity, it is likely that the satellite will be pointed at $20 \pm 5^{\circ}$. The atmospheric absorption of this has an approximate correlation of 0.999704 with the absorption at nadir, suggesting minimal effect within signifiant bands.

2.5 Automation

In order to automate DART, and the atmospheric modelling pipeline, we are building an algorithm using Pytools4dart. This algorithm will simulate the scene with DART without requiring manual input for each run and will intefacce with the model entirely through the Python library. By automating our pipeline we plan to minimise human error and reduce the time needed to run multiple simulations with varying results, and streamline the output compilation. This will help get more accurate results and save time with sensitivity analysis and parameter changes that could be required, for example, the case of brown pigments which were not present within the Lopex93 dataset.

3. Site Specific Considerations

3.1 DART Soil Model

DART uses scene models that simulate both the bi-directional reflectance factor (BRF) and brightness temperature factor (BTF) of a surface. It has three primary BRF models: Empirical and semi-models, geometric optical (GO) reflectance models, and Radiative transfer models (RT). The empirical models do not attempt to explain the biophysical parameters and processes that govern BRF and BTF, rather they give a mathematical description of observed patterns in BRF/BTF datasets. The semi-empirical models rely on simplified physical principles of GO and RT theory. These models are primarily used to understand the BRF of forests, and similar dense vegetation canopies. They rely on a prescribed combination of the foliage "crowns," the material(s) composing the forest floor, and the effect of the tree shadows. RT models, on the other hand, simulate the propagation of radiation through matter with all physical mechanisms caused by each endmember. The simulation of BRF involves 4 RT components: a soil model, a leaf model, a canopy model, and an atmospheric model.(Philippe, 2021) The theory behind the soil model is based on Bidirectional reflectance spectroscopy, (Hapke, 1981) it does not require either empirical expression or involve extensive computation time, as it is based on radiative transfer equations. This was verified through experimental evidence of the efficiency of the theory considering typical surfaces that are usually encountered during laboratory work and ground truth operations. (Hapke, 1981)

3.2 Soil Model

DART permits selection from a wide variety of optical properties related to different soil models. These were narrowed down with consideration given to the applicability of the model to our imaging conditions and their effectiveness in modeling properties relevant to our use case. This left us with three candidate models: Hapke, RPV (Rahman-Pinty-Verstraete), and Lambertian. The Hapke model had historically struggled to simulate RWC (relative water content) (Ding et al., 2024), a key consideration for the FINCH mission (Armstrong et al., 2025) and the provided details were insufficient to determine whether DART's Hapke model had been adjusted for this. The model itself was more suited for fluid and planetary modelling, on a much larger scale than our use case, and as such was determined to not be ideal for our purposes. The RPV model would require the calculation of soil reflectance anisotropies to be used. (Biliouris et al., 2009) Considering the various soil types, and their anisotropies, it would be too computationally strenuous to model each soil type, especially considering the lack of significant benefit over the alternatives given and, again, the scale of the imaging. In the end we selected a simple Lambertian definition for soil reflectance. The imaging site for the FINCH mission is tilled farmland, and therefore at first glance, is a surface that is not ideally modelled by Lambertian reflectance, and customized soil optical properties would need to be defined, however, the tillage can be modelled separately by DART as a sine wave. Therefore the soil reflectance can be initially modelled as flat, with DART adding both the topography and the sun-sensor geometry to the model. The Lambertian model is most effective when modelling a relatively flat surface that is chaotic on the small scale, such that light is evenly distributed, a state of affairs that suits soil within a reasonable margin of error. (Tu et al., 2017) The optical properties specified in the DART Lambertian soil model are based on light transmission and reflectance. We assume that soil would have no transmission, as the path of a light ray would be entirely intercepted by the ground, which allows it to only be absorbed or reflected. Diffuse reflectance was assumed to be much greater than specular reflectance, due to the rough composition of tilled soil. To model the soil's spectra, the diffuse reflectance at each wavelength was specified using 10 different pure soil spectra from our data. Each source has a different RWC which is inversely proportional to the reflectance of soil at each wavelength (Baumgardner et al., 1986).

3.3 Cloud Cover Model

The FINCH mission seeks to use hyperspectral sensor imaging to estimate crop residue cover, focusing on peak crop planting seasons. To account for all environmental factors affecting FINCH's ability to retrieve crop residue signals, atmospheric and cloud cover composition must be factored and modelled accordingly. To achieve this, DART was chosen as the primary radiative transfer model as it can model cloud volume and horizontal radiative transport effectively. DART enables the implementation of exponential random overlap due to the 3D radiative transfer model, accounting for the heterogeneity between cloud layers more effectively than MODTRAN (Lebrun et al., 2023). As such, DART is better-suited for modelling comprehensive cloud cover simulations and has motivated the shift from MODTRAN.

The cloud cover model seeks to evaluate atmospheric conditions, more specifically cloud coverage during the peak growing seasons at the imaging site. This is explicitly necessary to the FINCH mission as aerosols such as clouds directly alter the trajectory of solar and impact the diffuse radiation received by the surface, serving as optical impedance (Kalay, et al., 2022). This motivation emphasizes the focus on simulating cloud cover during mid-spring and mid to late summer. The seasonal bounds of the growing season is set to be between the first and last days of temperatures reaching 0C or below. However, examining the mid points in each season is more effective and reduces seasonal outliers, lowering the amount of simulations required to account for such extreme seasonal conditions. This results in the following cloud cover scenarios: spring day and night, summer day and night. For daytime simulations it is logical to evaluate periods of peak solar radiation which occur at solar noon; hence the simulations are modelled around 12:00 (Fernández-García et al., 2010). The nighttime simulations for spring and summer can be set around 20:00-23:00, when the sun is set. This establishes a baseline for the simulations where there is no solar radiation reaching the surface, corresponding in a total flux of zero. (Fernández-García, et al., 2010).

To effectively model the atmospheric conditions that impact radiative transfer, DART accounts for the spherical geometry of the Earth, correcting the optical depth path of photons for directions off the local vertical (Philippe, 2021). However a plane parallel approximation is applied to the individual cloud layers treating them as horizontally homogenous which simplifies the simulations to allow for more computationally efficient 1D radiative transfer models (Di Girolamo et al., 2010). DART accounts for two components of the flux products with that being the upward and downwards fluxes using Earth-Atmosphere coupling (Philippe, 2021). By setting both flux components to total, the model accounts for both diffuse and direct radiation, encompassing the total solar radiation value (Kalay et al., 2022).

FINCH's mission targets farmland and is the driving motivation behind using the RURALV23 aerosol property parameter. This aerosol model is most appropriate for considering crop residue in rural farm clear sky conditions and aligns with FINCH's objective for agricultural based observations. Using this model establishes a baseline for radiative transfer simulations without clouds. Once this baseline is established, the cloud scene can be implemented. During the spring simulations, the atmosphere is in a transition period dominated by both stratus and cumulus clouds as there is a mix of overcast, rain, and fair weather throughout the season. For summertime simulations, cumulus clouds which are more synonymous with fair weather, were emphasized as they are dominant during that season.

The atmospheric model has 3 levels: low-atmosphere (LA), mid-atmosphere (MA), and high-atmosphere (HA), emphasizing MA and HA for cloud coverage modelling. The quality of pushbroom sensor imagery has been shown to significantly degrade under the influence of clouds, as they make it difficult to locate exact image points when using feature-based image matching (Wang et al., 2008). This effect is a result of the clouds' ability to impact radiative transfer and obscure surface features. As such, cloud heterogeneity and sensor geometry must be carefully considered when modelling the cloud coverage over the imaging site.

Clouds are complex phenomena whose formation, spatial structure and variability occurs at scales smaller than typical grid resolutions implemented in radiative transfer models (Matus et al., 2017). The complex microphysics of clouds cannot be truly resolved and must be represented through parametrization. This is a key issue that must be addressed when parametrizing clouds which is also supported in work done by Lebrun et al., (2023) on vertical cloud heterogeneity, which suggests that radiative errors are highly dependent on vertical cloud layers. When the vertical cell component is too large it smooths out cloud layer geometry, masking the true vertical separation between layers (Lebrun et al., 2023). Having poor vertical overlap estimations results in a high degree of cloud albedo error, skewing overall simulations (Lebrun et al., 2023). Cell dimensions for the MA were selected to be dx=100 m, dy=100 m, dz=500 m based on suggestions from the DART user manual (Philippe, 2021). This is consistent with the previously mentioned works, as the vertical component dz= 500 m serves as a reasonable compromise that allows large scale vertical layers to be distinguishable, but the subgrid homogeneity between layers must still must be parametrized. For the simulated sensor, the z-component grid size was determined to be 85,000 m to account for the lower limit of the HA. These parameters give us reasonable estimations to simulate FINCH's cloud coverage during the time of the mission.

Factor	R^2	Correlation
Cumulus	0.787517976	0.887422096
Stratus	0.786496492	0.886846374
Aerosols * 10	0.999183537	0.9995916853
Aerosols * 20	0.997628059	0.998813326

Table 1. R^2 and correlation for stresses added to an atmospheric model.

3.4 Atmospheric Composition

Accurate modelling of site specific atmospheric composition within clearly defined margins of error plays a vital role in any attempted hyperspectral remote sensing, due to the complex nature of the interaction of gases and aerosols with the radiative transfer between the Earth's surface and the sensor.

The scattering and absorption of radiation by gases and aerosols, in various atmospheric layers irreparably changes the spectral signature of detected light, therefore potentially obscuring the features used to identify crop residue and other surface materials of interest to the mission. Agriculturally active regions are known to have a complex atmospheric environment due to the emission of reactive nitrogen species and other smaller quantities of gases related to other agricultural activities. Specifically, fertilizing, livestock activities, and soil microorganisms are known to release large quantities of nitrogen - containing compounds, such as ammonia (NH3), one of the major reactive nitrogen species in the agricultural atmosphere (Luo et al., 2025; Pan et al., 2022).

Data obtained from previous satellite remote sensing missions, have shown that atmospheric ammonia concentrations are consistently high over some of the world's major agricultural regions, showing that agricultural emissions have observable influence on local atmospheric chemistry. (Warner et al., 2017) These emissions not only impact the atmospheric nitrogen cycles, but also the aerosols and radiative activity that affects atmospheric transmission and scattering.(Fung et al., 2022) The vertical profile of ammonia and other nitrogenous gases adds more complexity to the attempts at atmospheric modelling for the FINCH mission. Changes in atmospheric mixing and chemical transformation processes may cause heterogeneous concentration profiles of these gases. These might have an influence on the interactions of radiation with the atmosphere at various altitudes (Liu et al., 2025). Apart from nitrogen compounds, the agricultural environment may also have trace quantities of high spectral impact gases and aerosols resulting from the use of pesticides and fertilizer. These chemicals not only contribute directly to the complexity of the atmosphere, but affect the formation of expected aerosols. (Jackson et al., 2025) Although the net concentration of these chemicals in the atmospheric column may be less than the main gases present in the atmosphere, these chemicals make an outsized contribution to the overall image and are mainly a factor of lower altitudes. Land use in agriculture is also an indirect influence on the radiative properties we are considering, through its effects on surface albedo as well as influence on land-atmosphere interaction. Changes in the types of crops grown, soil exposure, and the residue on soil surfaces causes clear change in both the net reflectance, and the spectrum that is reflected off of the surface. (Starr et al., 2020; Sieber et al., 2022) These interactions must be accounted for in our simulations, given our sensor sensitivity, noise tolerance, and the possible effect on unmixing. In order to account for such atmospheric effects within the FINCH atmospheric inversion pipeline, we estimate specific abundances of trace atmospheric material, fitting it within the standard atmospheric composition model for the scene that we use, which is then added into the radiative transfer models and simulations that are conducted to produce transmittance spectra. The uncertainties inherent in this must be pointed out, as without reliable atmospheric testing, this can only be an estimate. These considerations were added onto a rural mid latitude summer atmospheric model built into DART.

When testing the effects of high methane and ammonia concentrations in the model we multiply the existing atmosphere concentration by an estimated amount, largely based on, at this point, an intention to understand the effects rather than create an accurate model of these particular stressors. The results of this can be seen in Table 1 and Figure 3, for 10 and 20 times the concentration of these molecules that were present in the mid latitude summer atmospheric model provided by DART. While the difference is very clearly visible in this case, and the results show insignificant change, even this would have to be accounted for, and when conducting operations, it is highly likely that the concentrations will be significantly higher, and require more precise estimation.

3.5 Tillage

Accounting for soil tillage in surface models of agricultural sites is vital to properly modeling the albedo of the surface at the time of imaging, as there is significant effect on the reflectance spectra of the site. (Oguntunde et al., 2006) This is done here in two ways, with SALBEC (Soil ALBEdo Calculator) (Jasiewicz and Cierniewski, 2021), and with topography options in DART. In the case of models produced with SALBEC, the library is fed with a pure endmember soil spectrum from our dataset, as well as the imaging location and time of interest as well as numerical approximations of tillage depth and density at the site and estimated uncertainty to arrive at a model of the albedo .of the soil for the day in question. This is being used, at present, to validate data simulated with DART. Our surface models using DART are based on a built in spectral library, and options to vary surface composition abundance and topography. In modeling tillage we, for the lack of a better option, create a topography that follows a sine wave with an amplitude of 0.125m, that matches, or is otherwise equivalent in effect to, data provided by EMLI Innovation Farms as part of our initial data collection. (Armstrong et al., 2025)

3.6 Vegetation

When modelling soybean($Glycine\,Max\,L.$), Dart requires several inputs of numerical estimations of bottom height, average height, standard deviation and leaf area index, as well as an input database of vegetational optical properties. Using different resources, these values are estimated by taking the mean of commonly recorded values. The vegetation optical properties are then directly calculated using Pytools4dart and the Prospect model.

The minimum height for the soybean plant is chosen to be $0cm$ while the average lowest leaf height is estimated to be $12cm$((Manitoba Pulse & Soybean Growers, 2019)). The average height of a soy bean itself is taken to be $100cm$((Nleya et al., 2019)). For simplicity the standard deviation is taken as 0, as there is no ground truth data available. The leaf area index itself is calculated thus:

$$LAI = \frac{TotalLeafAreaofaSpecies}{GroundArea} \tag{1}$$

(Rapson, 2018) Therefore LAI can simply be calculated by knowing the number of soy bean plants, average number of leaves on a plant, average area of a leaf and the area that is being modeled. Finally the scene is modeled such that it has multiple rectangular areas with width of average plant width of a soybean and length of the measured area. These rectangulars have then been placed on the scene such that they had $38cm$ spaces between them as it is the average suggested row width for soybean((Fogelberg, 2021)).

The Prospect Model is a radiative transfer model based on a generalized "'plate model" that represents the optical properties of plant leaves from $400nm$ to $2500nm$. It models scattering using a spectral refractive index as well as the leaf structure, it also models absorption through the use of pigment concentration, water content and spectral absorption coefficients(Jacquemoud and Baret, 1990). In our model leaf structure(defines the compact layer of leaf mesophyll), Chlorophyll content(concentration of green pigments), Carotenoid content(concentration of yellow/orange pigments), Anthocyanin content(concentration of red/purple pigments), concentration of brown pigments, the amount of water per unit leaf area and the concentration of dry organic matter are used to calculate the vegetation optical properties of soy bean. These numerical values are taken from the Lopex93 database((Hosgood et al., 1993)). To create a database using Prospect, the lowest and highest values of each parameter were taken from the database to create random sets of data using those values as thresholds. Values are chosen such that leaf structure is between 1.72-2.10, Chlorophyll content is 1.360-1.361$\frac{\mu * g}{cm^2}$, Carotenoid content is 5.150-5.151$\frac{\mu * g}{cm^2}$, Water per unit area is 0.0021-0.0080$\frac{g}{cm^2}$, concentration of dry organic matter is 0.0031-0.0035$\frac{g}{cm^2}$. In the database Anthocyanin content is given as $-999\frac{\mu * g}{cm^2}$ for all plants thus it is assumed to be 0 in our calculations. Finally as Prospect model had not included concentration of brown pigments until 2017 Lopex93 database has no data on it. Therefore it has been left out of our calculations.

4. Results

In conducting this study into atmospheric modeling for this particular mission, our aim is to facilitate the mission parameters both through providing atmospherically propagated data for model training and creating a pipeline for the atmospheric correction of satellite data from FINCH. To properly do this, we need to create an atmospheric model that allows for precise inversion of the atmospheric and ground effects of data taken of our imaging site, to account for more sensitive spectral features to be isolated. This has been done effectively by the modeling team, and has been compiled into a reasonable model of atmospheric effects that allows for further calibration based on information from grand truth operations such as low atmosphere composition, and imaging time specific effects such as cloud cover. This model is being integrated into our current data processing pipeline as a comprehensive method for inverting major effects caused by phenomena occurring between the leaf and the lens.

5. Conclusion

The atmospheric model for FINCH is based on currently understood site conditions for a particular farm, as well as data for particular plant species that we intend to image. However, it also allows for many other things to happen. By modifying it, we are capable of Imaging with a high degree of accuracy, a large number and variety of sites, beyond the mission criteria. This also serves as a general model for agricultural remote sensing in the SWIR1 band, particularly as template for other small satellite remote sensing groups who may wish to use this underutilized band, and lack the capability to develop one. Most critically, developing this process has allowed for a group of undergraduate students to achieve semi-proficiency in areas remote sensing and atmospheric radiative transfer in a manner that they would have not otherwise had access to at the university.

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This paper would not have been possible for the dedicated work of the Unmixing and Deep Learning teams of UTAT SS Science. We must point out that this project is one component of, and the result of work done by the countless members of the University of Toronto Aerospace Team Space Systems Division, over the course of several years as we developed the FINCH, HERON mk.1, and HERON mk.2 cubesats, and to the other members of the Science subsystem, both current and former who worked on every aspect of the mission so that we could reach this stage. We would like to thank the collaboration from EMLI Innovation Farms and AAFC that we have received for providing data vital to our process.

7. Figures

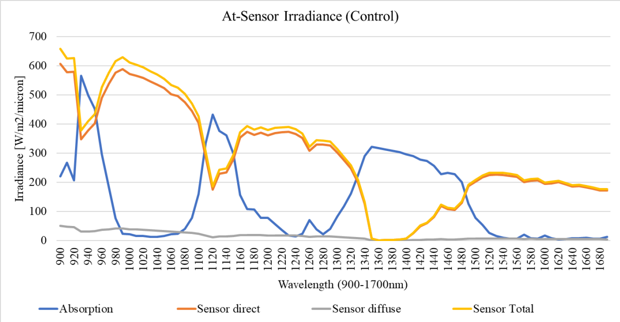

Figure 1. A plot of atmospheric absorption and at-sensor irradiance from 900-1700nm.

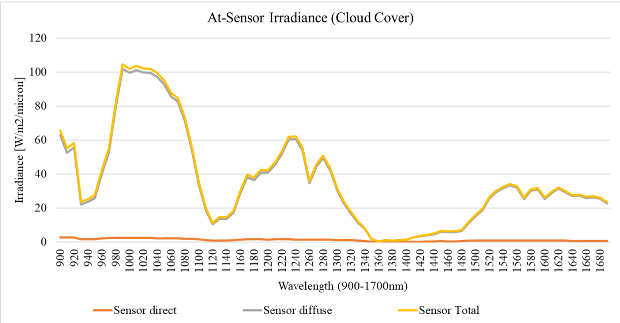

Figure 2. A plot of atmospheric absorption and at-sensor irradiance from 900-1700nm with an average cumulus cloud obscuring the imaging site.

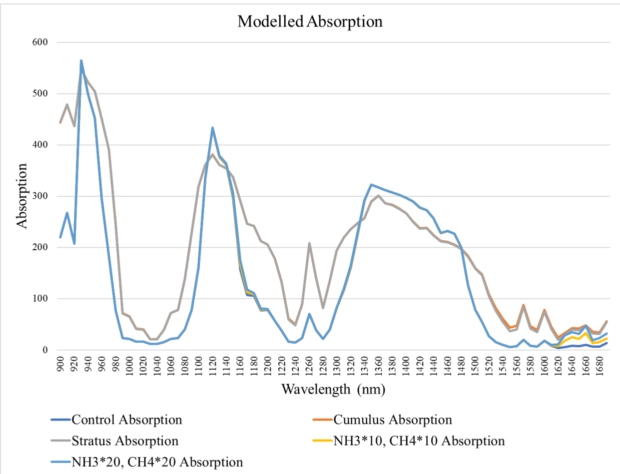

Figure 3. A plot of atmospheric absorption from 900-1700nm given multiple stressors.

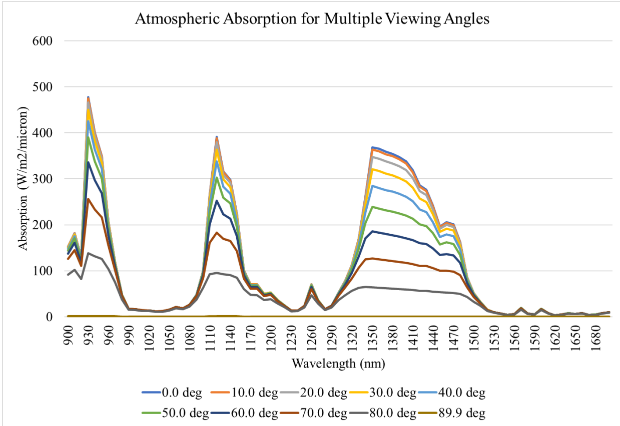

Figure 4. Atmospheric absorption at multiple viewing angles relative to nadir.

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