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Habitat Suitability Modelling for Northern Goshawk in the Lillooet River Valley Using Geospatial Data

Tsetspa7 Forestry LP

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Abstract

This project developed a habitat suitability model for the Northern Goshawk (*Accipiter gentilis*) in the Lillooet River Valley, British Columbia, to support conservation efforts through advanced geospatial analysis. The study integrated Light Detection and Ranging (LiDAR), Vegetation Resource Inventory (VRI), and Geographic Information Systems (GIS) with Maximum Entropy (MaxEnt) modelling to identify critical habitat characteristics and predict high-suitability areas. Three MaxEnt models were developed: Model 1 (12 original occurrence points), Model 2 (212 points, including 200 synthetic), and Model 3 (23 original occurrence points). Model 3 emerged as the preferred approach, providing the most detailed habitat insights by fully leveraging LiDAR-derived variables across the entire study area. Results classified the study area into low (55.37%), medium (28.95%), and high (15.68%) suitability zones, with high-suitability areas concentrated in mature coniferous forests. Deliverables include habitat suitability maps, R scripts, and this report detailing methodology and results. This project highlights the value of integrating geospatial data and ecological modelling in the conservation of Northern Goshawk habitat in British Columbia, specifically within the Tsetspa7 Forest Licence area.

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Background

The Northern Goshawk (*Accipiter gentilis*) is a large forest raptor and apex predator, occupying a crucial role within temperate forest ecosystems (Wright et al., 2022). Its habitat requirements are highly specific, depending on factors such as forest composition, elevation, stand age, and tree height (Mahon, 2025). As an indicator species, the Northern Goshawk reflects the health of its habitat. The coastal subspecies (*Accipiter gentilis laingi*) is listed as threatened under the federal Species at Risk Act (SARA) and is also provincially red-listed in British Columbia (Wright et al., 2022). Its dependence on open, mature, and old-growth forests for foraging and nesting makes it particularly vulnerable to habitat loss due to logging and other forest management activities (Mahon, 2025). Due to these habitat requirements, the coastal subspecies faces a high risk of population decline, threatening its long-term survival in coastal British Columbia (Mahon, 2025).

The habitat of the Northern Goshawk is influenced by various factors, including the availability of large, undisturbed forested areas that provide cover, foraging opportunities, and safe nesting sites (Wright et al., 2022). Additionally, forest management practices that do not account for the specific habitat requirements of the Northern Goshawk contribute to the decline in habitat quality, increasing the risk to the species. Therefore, identifying and protecting critical habitats for the Northern Goshawk is essential for its conservation (Wright et al., 2022; Mahon, 2025).

The protection of Northern Goshawk habitat often creates significant conflicts with timber harvesting operations, resulting in costly replanning, delayed operations, and reduced harvestable area (Mahon, 2025). These economic challenges highlight the need for proactive planning methods that can anticipate goshawk habitat preferences before harvesting activities begin. By identifying potential nesting sites in advance, forest managers can develop integrated management strategies that balance conservation requirements with sustainable forestry practices, reducing both ecological impacts and economic disruptions (Wright et al., 2022).

Habitat suitability modelling is a valuable tool for guiding conservation and forest management strategies by predicting the potential distribution of species within an area. For species like the Northern Goshawk, whose habitat is in decline, these models can help inform conservation strategies by identifying areas that should be protected (Wright et al., 2022). One widely used and effective technique for habitat suitability analysis is MaxEnt modelling. This approach allows researchers to identify critical habitat features and assess the potential impact of land use changes on species conservation.

LiDAR has become an essential resource in habitat suitability studies. When combined with VRI data, which offers detailed information on forest composition and age classes, these datasets enable a comprehensive analysis of habitat conditions. Geographic Information Systems enhance the ability to analyze multiple spatial datasets, supporting evidence-based decisions for conservation and resource management (Wright et al., 2022). GIS tools enable the visualization of habitat suitability and spatial analysis of environmental variables.

Objectives

The goal of this project was to develop a habitat suitability model for the Northern Goshawk (*Accipiter gentilis*) in the Lillooet River Valley. The model was used to identify key habitat characteristics and predict areas where suitable habitat was most likely to occur. The objectives of the study were to: (i) assess the habitat suitability of the Northern Goshawk using environmental and ecological variables, (ii) evaluate the impact of forest structure on habitat suitability, (iii) develop habitat suitability maps using MaxEnt modelling to classify areas as low, medium, or high suitability, and (iv) integrate LiDAR, VRI, and GIS to refine the model.

Methods

Study Area

The study area is the Tsetspa7 Forest Licence, located within the Sea to Sky Forest District. The project site is north of Harrison Lake, extending east of Golden Ears Provincial Park and southeast of Lillooet Lake, in the lower Lillooet River valley. Access to the area is via Duffey Lake Road (Highway 99) and the Lillooet River Forest Service Road (FSR). Figure 1 shows the geographic extent of the licence area.

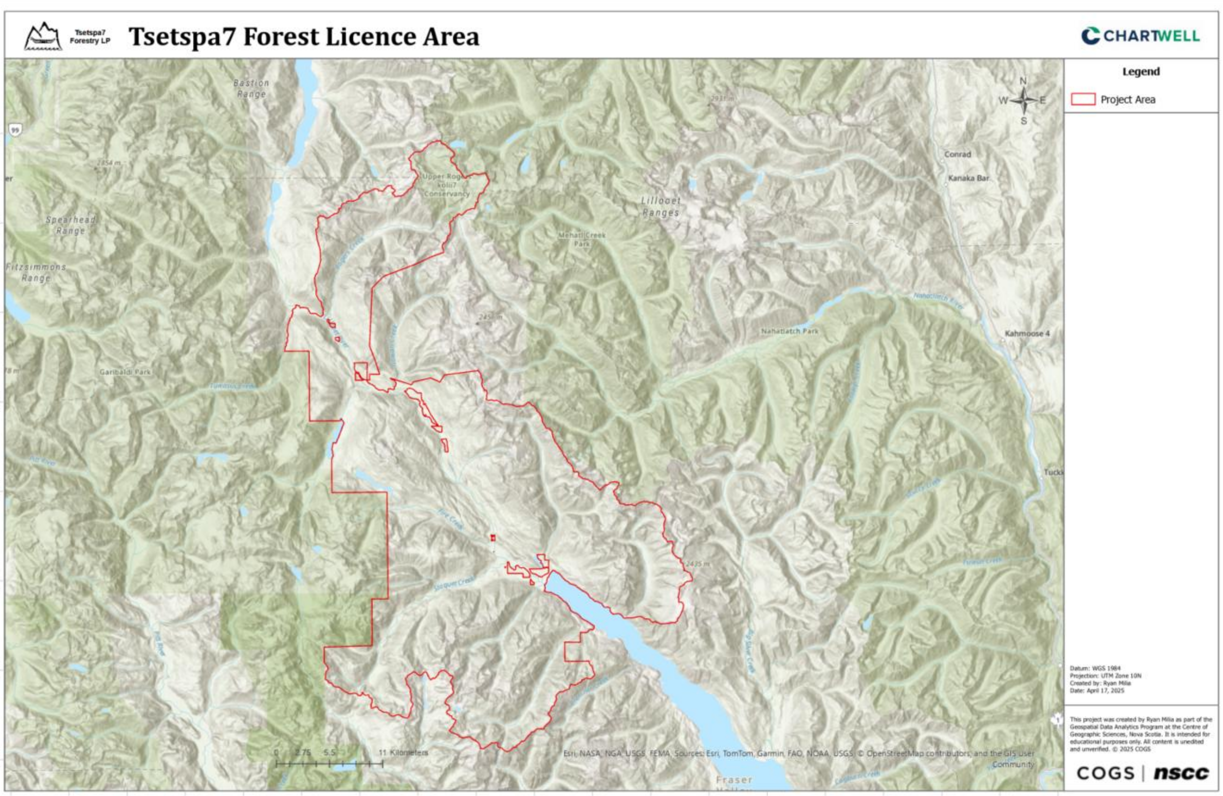

Figure 1. Extent of Tsetspa7 Project Area: Boundary is shown within the red polygon

Data Description

This study utilized multiple geospatial data sources to develop a comprehensive habitat suitability model. LiDAR data, provided by Tsetspa7 Forestry, supplied detailed topographic information including elevation and canopy height in LAZ and LAS formats. Vegetation Resource Inventory (VRI) data, sourced from the British Columbia open data portal, provided essential information on vegetation cover, species composition, and forest age classes (Government of British Columbia, 2023). Species occurrence data was obtained from field observations and provided by Chartwell Resource Group LTD. To accurately represent the landscape, water body information was incorporated from Statistics Canada's "Water File - Lakes and Rivers" dataset, which allowed for the masking of water features from the analysis.

Data Processing

The processing workflow involved several strategic steps to prepare the data for habitat suitability modelling. First, 298 LAZ files were converted to LAS format using ArcGIS Pro's "Convert LAS" tool in a batch operation. Additional LAS files were unzipped using 7zip software, with all data stored on an external drive due to the significant storage requirements. The VRI dataset processing involved clipping three datasets to the project boundary, with only the VEG_COMP_LYR_L1_POLY dataset retained for analysis. Unnecessary fields were removed to streamline the data and improve processing efficiency. Water features were masked from both LiDAR and VRI datasets by converting Statistics Canada water data to raster format and applying as a mask. The species occurrence data required conversion from KML to a vector point layer, followed by removal of duplicate points to ensure data integrity. Environmental variables were then extracted to these points using the "Extract Multi Values to Points" tool to enable model training.

Variable Generation

The generation of environmental variables aimed to create meaningful predictors for the Northern Goshawk habitat suitability model. From the LiDAR data, two Digital Elevation Models (DEMs) and Digital Surface Models (DSMs) were generated using the "LAS Dataset to Raster" tool and used to develop two Canopy Height Models (CHMs) via the "Calculate Raster" tool. These DEMs and CHMs were merged using the "Mosaic to New Raster" tool, reprojected to NAD 1983 UTM Zone 10N to address pyramid display issues, and clipped to the project boundary (converted from KML to SHP format) using the "Clip Raster" tool.

The Vegetation Resource Inventory (VRI) dataset was processed using Python to derive variables relevant to Northern Goshawk habitat, with all classifications based on British Columbia’s VRI definitions. Forest Type was categorized as coniferous (1), deciduous (0), or unknown (2). Crown Closure was defined as High (70–100%, 1), Medium (30–70%, 2), or Low (0–30%, 3). Stand Age was classified as Old Growth (100+ years, 1), Mature (40–100 years, 2), or Young (0–40 years, 3). Biogeoclimatic (BEC) Zones were assigned High Suitability (1) for CDF, IDF, ICH, and CWH zones (excluding vh subzones) based on goshawk habitat preferences, with all other zones designated Low Suitability (0). Vertical Complexity was excluded due to missing data in the northern project area. All variables were rasterized to a 5m resolution using the Polygon to Raster tool to match the resolution of LiDAR-derived raster layers.

MaxEnt Modelling

Three distinct MaxEnt models were developed in RStudio, each documented in separate markdown notebooks. Model 1 (*tsetspa7_model*) used the original 12 species occurrence points with a regularization multiplier (regmult) of 6 to reduce overfitting due to limited sample size. It incorporated three predictors: stand age, forest type, and BEC zone. Due to the limited species occurrence data, I decided to create a second model with additional synthetic occurrence points. Model 2 (*tsetspa7_synthetic_model*) expanded the dataset to 212 presence points by generating 200 synthetic points based on environmental similarity to the original occurrences. This model used a lower regmult of 2 to allow more model flexibility and included five predictors: stand age, forest type, BEC zone, DEM, and CHM. Model 3 (*tsetspa7_model_v2*) used 23 occurrence points and maintained the same five predictors as Model 2. This model incorporated the full extent of available LiDAR data across the project area, enabling a higher-resolution characterization of habitat conditions. A regmult of 1 was used, reflecting an increased confidence in the model's underlying structure and permitting more nuanced feature representation. Each model was calibrated to optimize the trade-off between model fit and predictive power, with regularization multipliers adjusted to mitigate overfitting while preserving ecologically relevant patterns.

Model Validation

Model validation included a combination of robust techniques to evaluate the performance and reliability of each MaxEnt model. Leave-One-Out Cross-Validation (LOOCV) was applied to all three models. For Models 2 and 3, which included larger datasets, K-Fold Cross-Validation was also conducted to provide more stable and generalizable performance metrics. A 70/30 train-test split was used across all models to assess sensitivity (true positive rate) and specificity (true negative rate). Area Under the Curve (AUC) values were calculated to measure each model’s ability to discriminate between suitable and unsuitable habitat, with higher values indicating better performance. Finally, the spatial distribution of predicted habitat suitability - classified into low, medium, and high categories - was compared across models to evaluate their practical implications for conservation planning.

Results

Data Processing

The processing of geospatial data presented several challenges. LiDAR data conversion and management required significant computational resources but was completed effectively despite storage and processing limitations. All LiDAR data was clipped to match the project area. The VRI data was classified using python and generated rasterized variables for forest type, crown closure, stand age, and BEC subzones, with the vertical complexity variable excluded due to significant data gaps. Extent misalignment issues between datasets were resolved using the "Resample" tool with the "Snap Raster" function, ensuring that all raster files shared identical spatial extent, resolution (5m), and projection (NAD 1983 UTM Zone 10N). Crown closure was later excluded from the modeling process due to its low predictive importance.

Model Performance

The three MaxEnt models exhibited distinct performance characteristics across validation metrics and habitat suitability distributions. To enhance resolution, each model's predictions were classified into both 3-level (low, medium, high) and 5-level (very low, low, medium, high, very high) suitability categories, with the 5-level distribution providing finer detail into habitat quality.

Model 1 (12 original occurrence points) showed high specificity in a 70/30 train-test split (presence: 0.3985; background: 0.0005). Leave-One-Out Cross-Validation (LOOCV) yielded an AUC of 0.9182, with a mean suitability at presence points of 0.7090. Its 3-level distribution was 42.31% low, 28.47% medium, and 28.22% high, while the 5-level distribution was 32.95% very low, 10.35% low, 28.47% medium, 7.76% high, and 20.46% very high. Model 1 demonstrated strong precision for the original occurrences but was limited by the small sample size.

Model 2 (212 points, including 200 synthetic) improved sensitivity (presence: 0.5122; background: 0.0870), with LOOCV AUC of 0.9567 and K-Fold AUC of 0.9500 (mean suitability: 0.5052). Its 3-level distribution was 47.94% low, 33.61% medium, and 18.44% high, and the 5-level was 40.96% very low, 6.99% low, 33.61% medium, 7.53% high, and 10.92% very high. Model 2's strong performance and broader distribution benefited from the larger dataset but relied on synthetic data.

Model 3 (23 original occurrence points) showed moderate performance (presence: 0.5204; background: 0.2606), with LOOCV AUC of 0.8267 and K-Fold AUC of 0.8249 (mean suitability: 0.5093). Its 3-level distribution was 55.37% low, 28.95% medium, and 15.68% high, and the 5-level was 48.66% very low, 6.71% low, 28.95% medium, 3.83% high, and 11.85% very high. Despite a lower AUC, Model 3 provided the most conservative and precise habitat characterization. Additionally, this model did not rely on synthetic data, making it less likely to overfit.

Habitat Suitability Maps

The habitat suitability maps generated from the three MaxEnt models revealed distinct spatial patterns in predicted habitat quality for the Northern Goshawk across the Tsetspa7 Forest Licence area. These differences reflected each model's underlying data and performance characteristics. Model 1 identified a relatively high proportion of high-suitability habitat, consistent with its strong presence-point precision but limited generalizability due to the small dataset. Model 2 produced a more balanced and widespread distribution of suitability, influenced by the expanded dataset including synthetic points. Model 3 provided the most conservative and spatially detailed delineation, with a higher proportion of low-suitability areas, shaped by the incorporation of LiDAR-derived predictors and a moderate sample size. This conservative distribution highlights Model 3's detailed habitat characterization, driven by the integration of additional LiDAR data. Comparative analysis of the maps revealed strong correlations between habitat suitability and key predictor variables, notably BEC zone (CWH/MH), forest type (coniferous), and stand age (mature and old growth), underscoring the relevance of these factors in shaping goshawk habitat preferences. The final habitat suitability map for Model 3, which offers the most spatially complete and precise delineation of potential habitat, is presented in Figure 2.

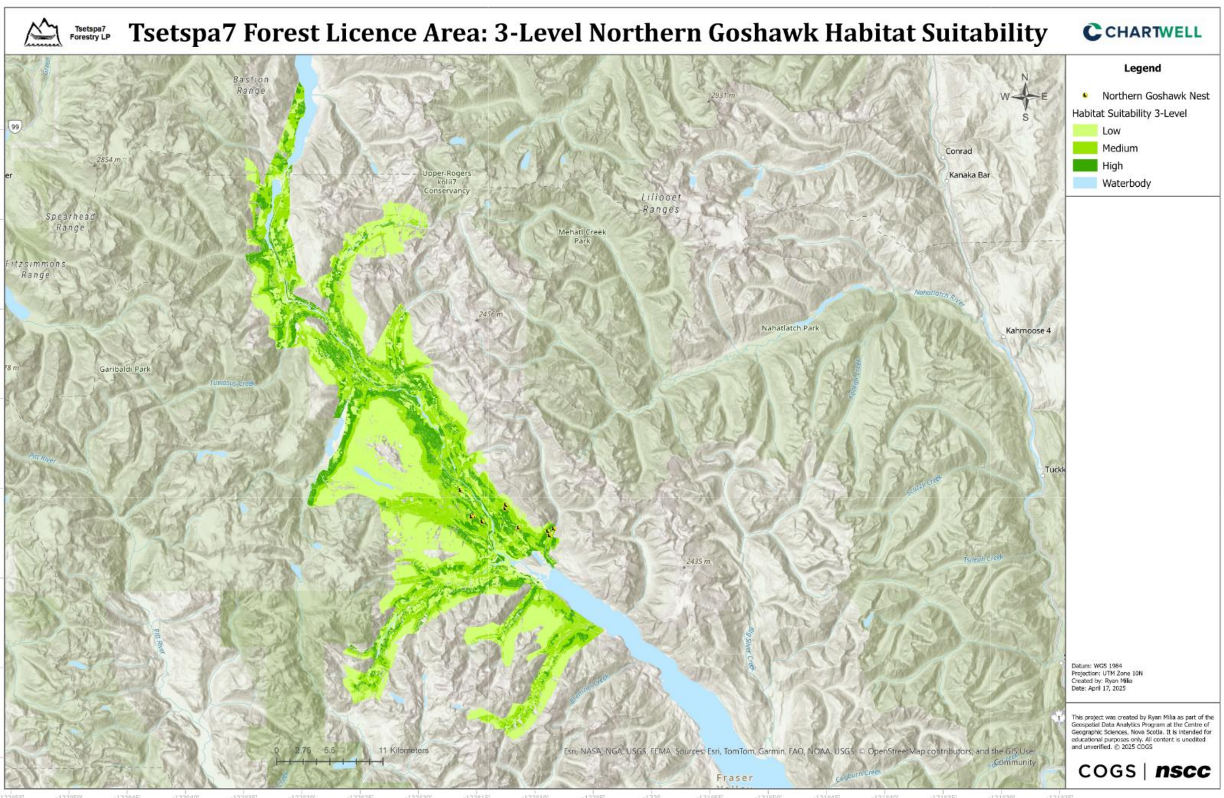

Figure 2. Final Habitat Suitability Map for Model 3.

Challenges

The development of the Northern Goshawk habitat suitability model presented several significant technical and methodological challenges throughout the project. Data processing, particularly the management of large LiDAR datasets, required considerable time investment and necessitated the use of external storage due to the substantial file sizes. Extent misalignment between different data sources presented a persistent challenge that required iterative application of "Extract by Mask" and "Resample" tools to ensure spatial consistency across all datasets. Data gaps were also an issue, particularly for the vertical complexity variable which had to be excluded from the analysis. The limited occurrence dataset in Model 1 constrained validation options and required careful interpretation of results. The computational intensity of processing was particularly evident during DEM and CHM creation, which took several hours and required careful parameter tuning to ensure accurate results.

Recommendations

Based on the habitat suitability analysis, conservation efforts should prioritize the high-suitability areas identified by Model 3, which covers 15.68% of the study area. Although Model 3 has a lower AUC compared to other models, its comprehensive LiDAR coverage offers the most spatially accurate representation of potential habitat across the project area. To improve model accuracy, additional field-verified occurrence data is needed to strengthen the statistical power of the model and reduce sampling bias that can affect model performance. Expanding this approach to other regions of British Columbia would support broader Northern Goshawk conservation, particularly for the threatened coastal subspecies. Using the final model to detect anticipated habitat enables proactive planning to balance conservation and sustainable forestry.

Conclusion

This project successfully developed habitat suitability models for the Northern Goshawk in the Tsetspa7 Forest Licence area through the integration of LiDAR, VRI, and MaxEnt modeling techniques. Among the three models developed, Model 3 emerged as the preferred approach despite its lower AUC (0.8267) compared to Models 1 and 2. Its preference stems from its utilization of comprehensive LiDAR coverage across the entire project area and its reliance on a larger set of original occurrence points (23), providing the most spatially complete and biologically relevant habitat characterization. The resulting suitability maps classify 15.68% of the study area as high suitability, 28.95% as medium suitability, and 55.37% as low suitability, offering a conservative but precise delineation of potential Northern Goshawk habitat. The methodology developed and insights gained aim to contribute to the long-term conservation of the Northern Goshawk in British Columbia, demonstrating the value of integrated geospatial analysis in species conservation efforts.

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Appendices:

Appendix A – Gantt Chart

Task	Start	End	Duration (days)	Status
Define Project Scope with CRGL	06-Jan-25	24-Jan-25	18	Complete
Literature Review	06-Jan-25	24-Jan-25	18	Complete
Project Proposal	06-Jan-25	31-Jan-25	25	Complete
Data Acquisition/Review	06-Jan-25	31-Jan-25	25	Complete
Data Processing/Cleaning	31-Jan-25	28-Feb-25	28	Complete
VRI Classification	14-Feb-25	25-Mar-25	39	Complete
Exploratory Data Analysis	14-Feb-25	28-Feb-25	14	Complete
Progress Report/Review	25-Feb-25	25-Mar-25	28	Complete
Preliminary Model Development	28-Feb-25	21-Mar-25	21	Complete
Preliminary Habitat Suitability Mapping	21-Mar-25	01-Apr-25	11	Complete
Preliminary Report Writing	01-Apr-25	13-Apr-25	12	Complete
Preliminary Presentation Preparation	01-Apr-25	13-Apr-25	12	Complete
Preliminart Report/Presentation Submission	14-Apr-25	14-Apr-25	0	Complete
Model Development/Tuning	13-Apr-25	20-Apr-25	7	Complete
Model Evaluation/Validation	20-Apr-25	25-Apr-25	5	Complete
Final Habitat Suitability Mapping	25-Apr-25	30-Apr-25	5	Complete
Compile Maps, Scripts, Model	01-May-25	05-May-25	4	Complete
Final Report Writing	05-May-25	19-May-25	14	Complete
Presentation Preparation	05-May-25	19-May-25	14	Complete
Submission & Review	19-May-25	19-May-25	0	Complete

Appendix B – Data Dictionary

Name	Description	Type	Source	Scale/Resolution	Coordinate System
VEG_COMP_LYR_L1_POLY_2023.gdb	Vegetation composition layer for Level 1 polygons in 2023	GDB	British Columbia open data portal	1:20,000	EPSG:32610 (WGS 84/UTM Zone 10N)
Tsetspa7 FNWL v2.kml	First Nations Woodlot Licence Area	KML	CRGL LTD.	1:50,000	EPSG:32610 (WGS 84/UTM Zone 10N)
Tsetspa7 GH Nests v2.kml	Species Occurrence Data for Northern Goshawk	KML	CRGL LTD.	1:50,000	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.shx	Shape index format for Project Boundary	SHX	CRGL LTD.	1:10,000	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.shp.xml	Metadata for Project Boundary shapefile	XML	CRGL LTD.	1:10,000	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.shp	Shapefile format for Project Boundary	SHP	CRGL LTD.	1:10,000	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.sbx	Spatial index for Project Boundary shapefile	SBX	CRGL LTD.	N/A	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.sbn	Spatial index for Project Boundary shapefile	SBN	CRGL LTD.	N/A	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.prj	Projection format for Project Boundary shapefile	PRJ	CRGL LTD.	N/A	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.dbf	Attribute format for Project Boundary shapefile	DBF	CRGL LTD.	N/A	EPSG:32610 (WGS 84/UTM Zone 10N)
Project_Boundary_v1.cpg	Code page for Project Boundary shapefile	CPG	CRGL LTD.	N/A	N/A
FC_CHM_WM_1m.tif	LiDAR derived Canopy Height Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
FC_DEM_WM_1m.tif	LiDAR derived Digital Elevation Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
HED_CHM_1m.tif	LiDAR derived Canopy Height Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
HED_DEM_1m.tif	LiDAR derived Digital Elevation Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
LillooetTuwassus_CHM_WM.tif	LiDAR derived Canopy Height Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
LillooetTuwassus_DEM_WM.tif	LiDAR derived Digital Elevation Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
TSE_CHM_1m_WM.tif	LiDAR derived Canopy Height Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
TSE_DEM_1m_WM.tif	LiDAR derived Digital Elevation Model	TIF	CRGL LTD.	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
WHS_562_5512_UTM10_SPO00-3461-02_APO00-3461-02_v1.laz	LiDAR data for specific area	LAZ	Tsetspa7 Forestry	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
WHS_546_5543_UTM10_SPO00-3461-02_APO00-3461-02_v1.laz	LiDAR data for specific area	LAZ	Tsetspa7 Forestry	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
WHS_545_5530_UTM10_SP000-3461-02_APO00-3461-02_v1.laz	LiDAR data for specific area	LAZ	Tsetspa7 Forestry	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
WHS_543_5548_UTM10_SPO00-3461-02_APO00-3461-02_v1.laz	LiDAR data for specific area	LAZ	Tsetspa7 Forestry	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
WHS_542_5538_UTM10_SPO00-3461-02_APO00-3461-02_v1.laz	LiDAR data for specific area	LAZ	Tsetspa7 Forestry	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
WHS_541_5542_UTM10_SPO00-3461-02_APO00-3461-02_v1.laz	LiDAR data for specific area	LAZ	Tsetspa7 Forestry	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)
WHS_540_5533_UTM10_SPO00-3461-02_APO00-3461-02_v1.laz	LiDAR data for specific area	LAZ	Tsetspa7 Forestry	1:10,000/1 m	EPSG:32610 (WGS 84/UTM Zone 10N)