

Using Time-lapse Imagery to Determine Snow Heterogeneity

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Abstract-

Snowmelt accounts for over 60% of water supplies in the western US. As a result, current seasonal streamflow forecasting relies heavily on snow water equivalent (SWE) and often neglects other hydrological processes. This can result in forecasting inaccuracies, such as the Colorado River experiencing a 19% decrease in streamflow since 2000 that is not explained by snowpack changes (Hogan & Lundquist, 2024). This suggests these other processes within the watershed may impact streamflow efficiency, defined as the amount of runoff per unit precipitation. This study will focus on snow heterogeneity (patchiness) as one such process. In patchy conditions, snow-free areas expose underlying vegetation to sunlight earlier. This increases evapotranspiration (ET) and potentially sequesters meltwater that would otherwise contribute to runoff. The amount of snowmelt lost to ET through this process is poorly understood and quantified. To test this hypothesis, time-lapse images were collected across various elevations and aspects in the East River Basin, Colorado. Through pixel value analysis, these images were used to assess snow patchiness and vegetation green-up (used as an indicator of ET) over the melt season. Outcomes may clarify how spring snow distribution affects runoff efficiency, improving water forecasting and management.

Introduction-

Snowmelt has a major influence on water resources in the western US, making up 53% of total runoff and 60% of total water supply (Li et al., 2017). Reliable predictions of streamflow are critical for water management, especially for the Colorado River basin, which supports 40 million North Americans (Fleck & Udall, 2021). Many seasonal streamflow forecasts rely heavily on snow water equivalent (SWE), which neglects other processes in the watershed but has historically been a decent predictor. However, since 2000, the Colorado River basin has demonstrated a 19% decline in average streamflow, while also delivering less water per unit snowpack (Fig 1) (Hogan & Lundquist, 2024). In the extreme case of 2021, an 80% average snowpack provided only 30% of average streamflow (Fleck & Udall, 2021). These observations challenge the reliability of SWE measurements alone to predict streamflow and suggest that there is a substantial gap in our current forecasting capabilities. To explain these discrepancies, we look to the unincluded processes for answers.

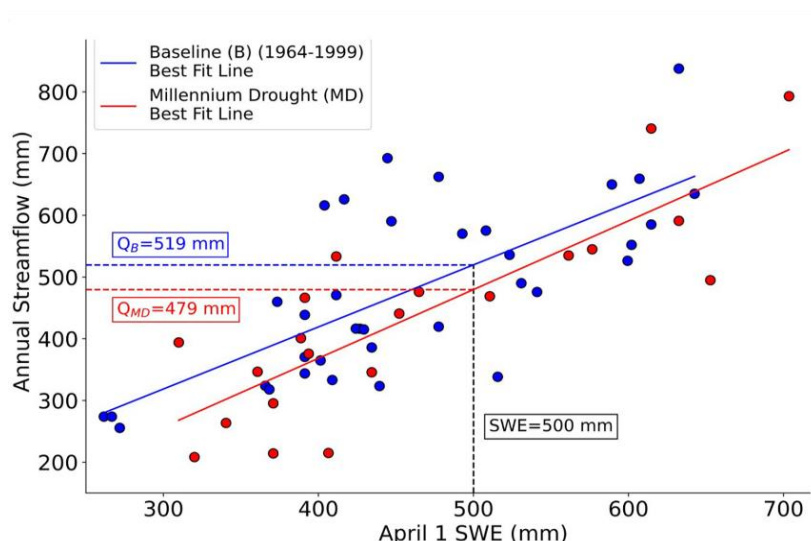


Figure 1: April 1 SWE snow course measurements (1964–2022) in Black Gore Creek basin and area-normalized annual streamflow (USGS gauge ID 09066000) in mm for baseline (blue) and Millennium drought (red) years. Using the best fit line, resultant streamflow estimates from 500 mm SWE are displayed in blue (baseline) and red (Millennium drought) boxes. Adapted from Hogan & Lundquist (2024).

Subsurface connectivity plays a key role in determining streamflow efficiency, defined as the amount of runoff per unit of input precipitation, and can be divided into two categories. Direct storage refers to a hydraulically connected subsurface that promotes streamflow efficiency (Grande et al., 2022), while indirect storage consists of disconnected reservoirs that instead support evapotranspiration (ET) (Dralle et al., 2018; Nehemy et al., 2021; Sprenger et al., 2016). The transfer of subsurface water

between these two storages is a critical factor in their dynamic effect on streamflow efficiency throughout the year and is dependent on subsurface connectivity. A saturated subsurface will increase meltwater transfer rates, increasing direct storage and therefore streamflow. On the other hand, dry soil barriers will limit this connectivity and may inhibit flow to streams (McNamara et al., 2005). This directly supports our hypothesis that snow cover distribution, specifically heterogeneous or patchy snow, can impact streamflow efficiency. In patchy snow conditions, meltwater may be absorbed by snow-free areas disconnected from direct storage, increasing evaporative losses rather than contributing to streamflow. In contrast, homogeneous snow cover encourages subsurface connectivity, enhancing direct storage and thus promoting more efficient runoff.

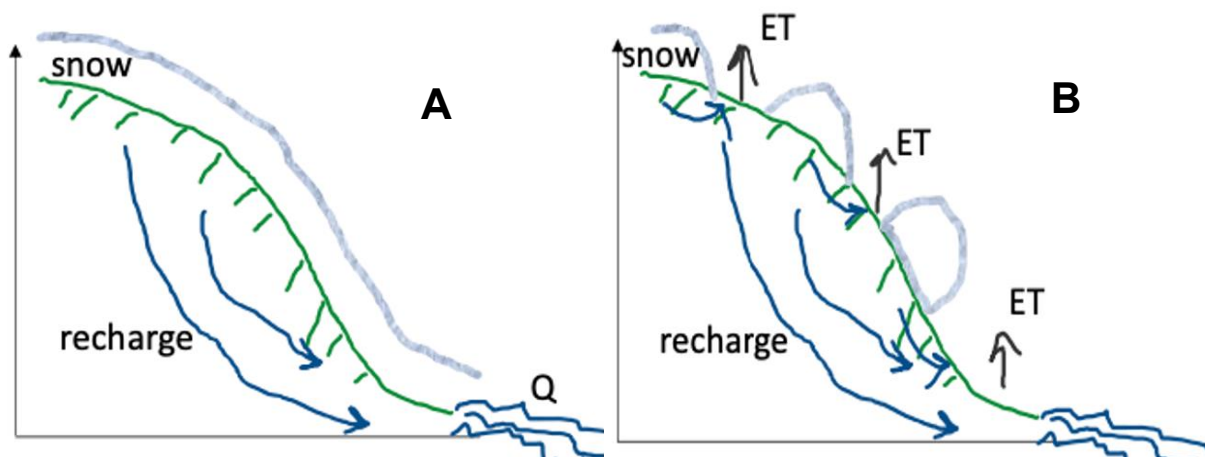


Figure 2: Conceptualization of impact of snow distribution on streamflow efficiency. (A) A uniform snow cover leaves no surface available to transpire, maximizing water transport to stream discharge (Q). (B) Some melting snow is absorbed by nearby snow-free areas in patchy snow coverage and is lost to ET rather than contributing to stream discharge.

To investigate if snow patchiness does in fact lead to less effective streamflow recharge and greater evaporative losses, we first needed quantify how snow patchiness varies throughout the year. Snow patchiness refers to the spatial fragmentation of snow cover, where in highly patchy conditions, there will be a greater potential for snow-free area to sequester snowmelt. Satellite-based methods have successfully estimated fractional snow cover area across large regions (Hall et al., 2006; Gascoin et al., 2020), which can then be used to determine snow patchiness. The objective of this project was to evaluate what smaller-scale, color imagery can add to what is already known from satellite imagery. This led to the following research question: How can color imagery from timelapse cameras best assess snow patchiness and vegetation green up, with green up being used as an indicator of ET? In doing so, we can begin considering snow

heterogeneity as a cause of recent year's discrepancies between snowpack and streamflow.

Methods-

Beginning in October 2023, time lapse cameras were installed at various elevations and aspects throughout the East River Basin (Fig 3). These cameras take 6 images per day, from 10am to 3pm on the hour.

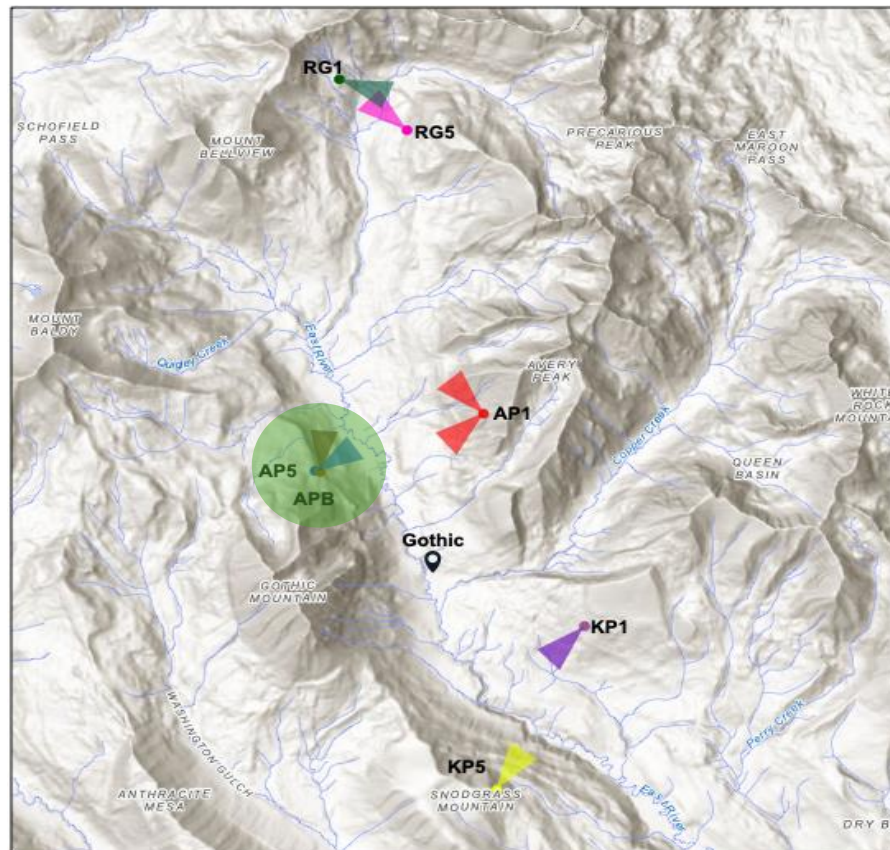


Figure 3. Locations of time lapse cameras throughout the East River Basin. AP5 and AP Bonus, green circle, provide imagery from October 2023 until June 2025. RG1, RG5, AP1, and KP1 have imagery from July 2024 up until June 2025. KP5 has imagery from October 2023 until August 2024.

Prior to analyzing these images, they must be filtered for quality control, where all frames that were determined to be problematic (over 10% of the frame is affected) for the analysis are excluded. This included mostly foggy days and images with significant glare. Then, for each site, a time of day was chosen which resulted in images with the fewest and most consistent shadow coverage. This subset of images was worked with for the remainder of the analysis. Once image filtering was completed, fractional snow

coverage was estimated from the images over the course of the water year, beginning on February 1st to specifically look at melt season.

Snow Identification

To ensure that only viable pixels (those where snow can possibly be detected) were considered, masking for trees and sky was performed. Sky masks were created using frames with clear blue skies, where bright sky pixels were isolated using an excess-blue index threshold of greater than 0.7. Tree masks were created using images with homogenous snow cover, where a unique value threshold was used to isolate trees, typically evergreens. To compensate for camera movement throughout the year, these masks were recreated and shifted when appropriate and applied to all frames.

For each frame, the remaining non-masked pixels were analyzed using a snow identification algorithm utilizing polynomial thresholding (PT). Unlike a static threshold, PT uses a second-order polynomial curve to dynamically determine thresholds, making it more robust and less susceptible to misclassifications from varying lighting conditions. This approach has been validated for this project's purposes in literature such as Burton-Johnson and Wyniauskij (2020), who applied PT to differentiate snow and rock classification from color imagery. Their study takes advantage of the difference in the pixel color of rocks, which reflect more in the red channel (R), and snow, which reflects more in the blue channel (B). Therefore, the R/B ratio (T), is expected to be greater for non-snow/rocks than for snow, and in doing so compensates for varying brightness by normalizing the channel's intensity.

However, Burton-Johnson and Wyniauskij's PT calibration used exclusively 'cloud-free' imagery. This inherently spans a narrow range of R-channel intensities, while our imagery includes a substantial number of frames captured under shaded conditions. As a result, their polynomial, which plots T against R, resulted in misclassifications for this project's data. In response to this, the fitting was inverted, instead plotting R against T. By swapping the positions of the R and T, the threshold can fully adapt across the full range of R intensities seen in many different lighting conditions. The coefficients were calibrated using snow and non-snow pixels in varying lighting, finalizing in the PT curve (Fig 4). These coefficients vary slightly for the two sites, however work consistently between the two years, likely due to differences in aspect and lighting.

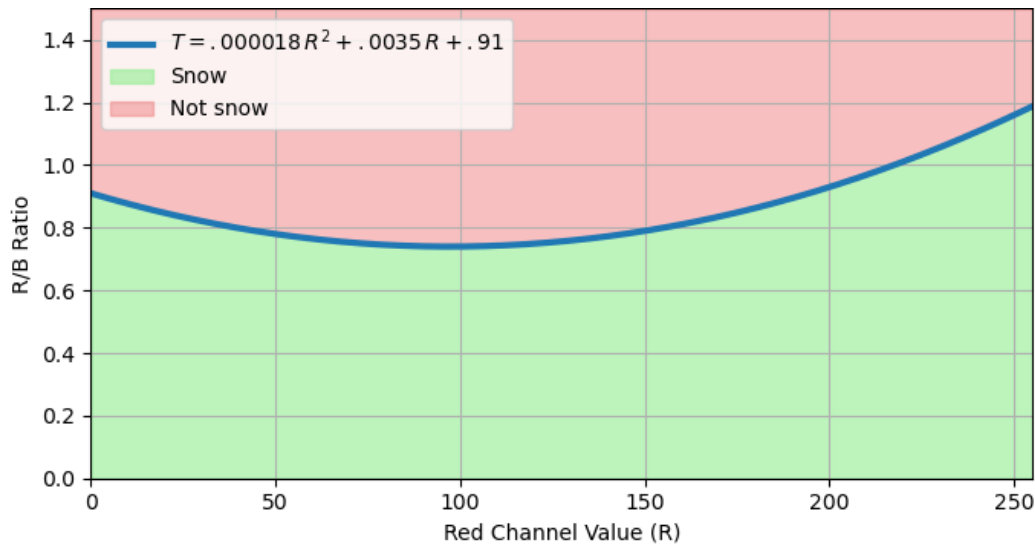


Figure 4. *Pixels with T (R/B ratio) values falling below the curve are labeled as snow, while those above are labeled non-snow. This curve is most strict for low to moderate R intensity, where snow and non-snow appear most similar, while becoming less strict as R increases, which consists of highly reflective snow under sunny conditions.*

In addition to the polynomial thresholding, pixels must also exceed static thresholds for whiteness and brightness. Whiteness must be greater than 0.63 and is defined as the quotient of the pixel's least intense of the three RGB channels and the most intense of the three ($\{\min(R,G,B) / \max(R,G,B)\}$). Brightness must be greater than 0.4 and is calculated using the pixel's HSV values. These supplementary thresholds were included to limit false positives, specifically from brights rocks. The output of this workflow is a binary mask made up of pixels classified as snow, non-snow, or masked (Fig 5). For a pixel to be classified as snow, it must meet all three criteria: below the polynomial threshold curve, above the whiteness threshold, and above the brightness threshold. All other pixels outside of the tree/sky mask are marked as non-snow. Morphology, or the smoothing of small specks and noise while preserving the mask's general shape, was not used as it introduced inaccuracies in the narrow gaps of the canopy.

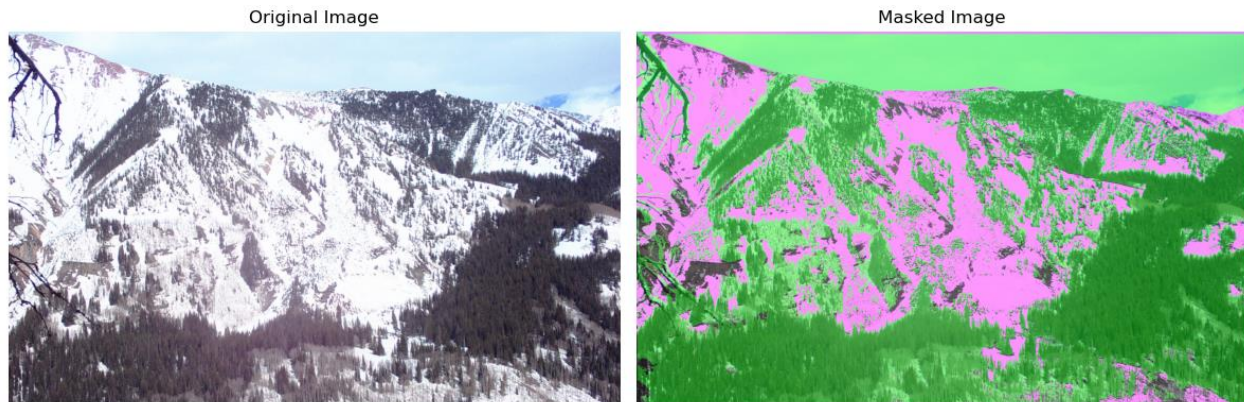


Figure 5. (left) Original frame. (right) Masked frame with pink representing snow, green representing the sky and tree masks, and all remaining pixels being non-snow.

Heterogeneity Quantification

While this binary mask is useful for analyses such as fractional snow cover area (fSCA), it does not directly answer the question of patchiness. Frames with identical fSCA can have completely different snow cover arrangements (Fig 6) and differentiating between these is crucial for effectively analyzing the effects of snow cover heterogeneity.

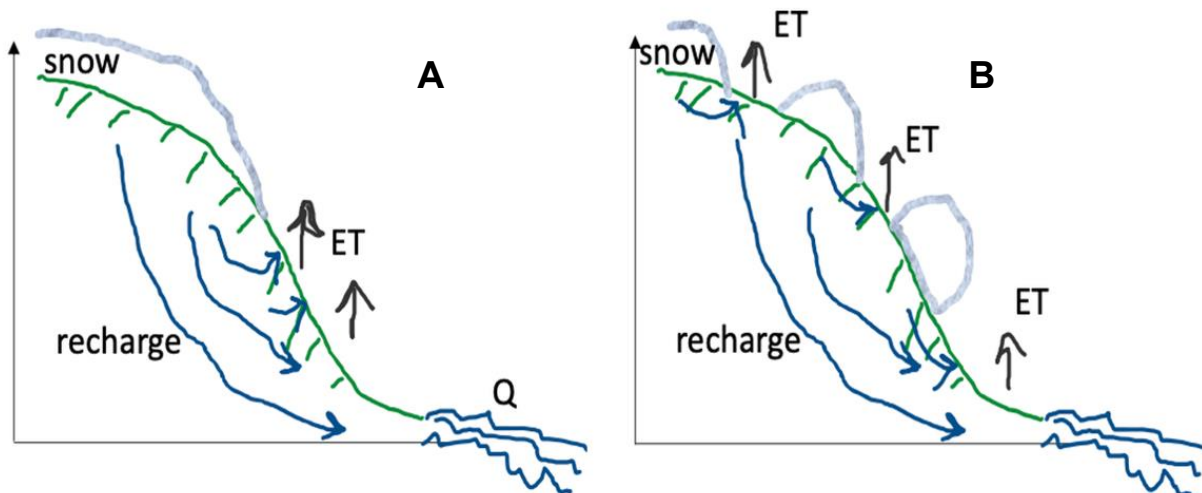


Figure 6. Illustration of similar fSCA resulting in different groundwater and ET processes. (A) represents an elevation gradient melt pattern, while (B) represents a more heterogeneous snow cover.

To address this issue, an index was created to take the series of these masks and quantify each frame's snow cover heterogeneity. To accomplish this, inspiration was drawn from landscape ecology's measures of connectivity, specifically aggregation metrics from the FRAGSTATS framework. Distance to nearest neighbor (ENN_MN) is well-documented as an effective predictor in landscape connectivity

(Keeley et al., 2021; Prugh, 2009). However, it computes the Euclidian edge-to-edge distance across all bare patches and averages them. In the context of snowmelt needing to travel the full distance to a bare pixel to potentially contribute to ET, this metric does not consider the entire the bare patch, only its closest edge. If a pixel is farther from the snow, it is less likely to sequester the meltwater. Instead, for each non-snow/bare pixel in the frame, its distance to the nearest snow pixel is calculated using SciPy's *distance_transform_edt*, and the average of these values is taken (D). The square root of D was used in the index to dampen extreme values in the late season. By considering the potential to sequester snowmelt for each pixel in each patch, this metric weighs in each pixel's potential ET and is more appropriate than ENN_MN. Additionally, it is more critical of an elevational snowpack (Fig 4a), with low elevation bare areas causing a higher D than the traditional ENN_MN would and returning a lower (less heterogenous) index.

Fahrig (2003) emphasizes that a metric of both patch abundance and their spatial arrangement is crucial for distinguishing fragmentation, advocating for the combined use of ENN_MN and the number of bare patches (NP). Similarly, Keeley et al. (2021) determined that these two metrics are among the simplest yet most informative. As a result, to pair with D's measure of isolation, NP is calculated using Skimage's *measure* and quantifies fragmentation. Because the snow identification algorithm described above neglects morphology, it leaves speckles of misclassified snow and non-snow. To compensate for this inflating NP readings, bare patches were redefined as being greater than 0.05% of the frame area.

Together, NP and D capture how many bare patches there are in the snow cover and where they occur. However, they cannot consider in the proportion of snow versus bare ground, downplaying patches while the landscape during snow dominance and over-amplifying when the landscape is most bare. This is something that landscape composition metrics fixed, using fractional bare area (fBA) and the fraction of snow-covered area (fSCA). FBA is calculated using the total number of bare pixels divided by the area of the image and is then raised to the 0.75 power. Similarly, the snow-covered area is included by taking the square root of the total number of snow pixels divided by area (fSCA). These sublinear exponents minimize rapid growth at extremes of snow and bare coverage and introduces a slight bias towards bare fragmentation. Additionally, division by A turns these values into a measure of density, keeping the index directly comparable across frames of different sizes. The product of fBA and fSCA will peak when neither is more dominant than the other, meaning a more heterogenous snow cover and appropriately regulating the index's output.

In summary, configuration (NP, D) captures the arrangement of bare patches, and composition (fBA, fSCA) captures how much bare and snow cover there is. By combining both, we get the following index formula:

$$Patchiness = \frac{NP \times \sqrt[4]{fBA^3} \times \sqrt{fSCA}}{\sqrt{D}}$$

Where:

A = frame area (pixels)

B = number of bare classified pixels

S = number of snow classified pixels

NP = count of bare patches >.05% of the frame

$$fBA = \frac{B}{A}$$

$$fSCA = \frac{S}{A}$$

D = mean bare-to-snow distance (pixels)

Greenup

To link snow cover heterogeneity to potential streamflow losses from ET, we use the seasonal rise in vegetation greenness (greenup) as a proxy. Leaf area expansion and stomatal activation, the two primary drivers of increased transpiration rates, directly manifest into increased chlorophyll content. Therefore, there is a positive correlation between greenness and ET rates (Kim et al., 2018). To quantify greenup from our imagery, we use the per pixel Green Chromatic Coordinate (GCC) defined as:

$$GCC = \frac{G}{R + G + B}$$

Similar to polynomial thresholding, by expressing green reflectance relative to total visible flux (R+G+B), GCC normalizes for brightness differences seen in the changing light conditions of sunny and cloudy days. Additionally, rather than simply analyzing if a pixel is green or not, it is continuous and determines how green it is. This is an important distinction when using it to quantify ET rates, which are also continuous. Richardson et al., (2018) has demonstrated that Green Chromatic Coordinate (GCC) measurements derived from near-surface imagery aligns closely with photosynthetic activity. Denham et al. (2025) and Young et al. (2022) also support using GCC as a predictor of daily ET. These results establish GCC quantified green-up as an effective proxy for ET in imagery-based studies.

For each frame in the time series, both the snow mask and the tree/sky mask is applied. These isolate vegetation eligible pixels, where it is possible for deciduous and herbaceous (seasonal) vegetation to appear. The tree mask is included specifically to exclude evergreen trees, which have insignificant changes in chlorophyll levels compared to ET activity and dampen the greenup analysis. Additionally, each frame is roughly cropped to a region of interest that focuses on vegetated areas and excludes areas such as rock outcroppings. The GCC of each of the vegetation eligible pixels in this region is taken (Fig. 7) and the mean of these values is taken as the measure of that frame's greenness.

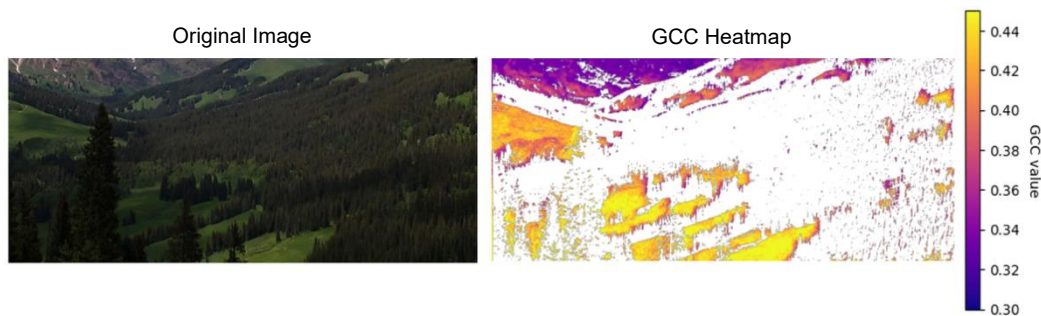


Figure 7. (Left) Original image cropped to “vegetation eligible” region. (Right) Evergreen and snow masked pixels shown in white, GCC pixels shown with heatmap.

Results

Fractional Snow Cover Area (fSCA)



Figure 8. fSCA curves for AP5 and APB across the 2024 and 2025 melt seasons. (Top) Observed fSCA from AP5 imagery for 2024 (February 1 – June 28) and 2025 (February 1 – June 1). (Bottom) Observed fSCA from APB imagery for 2024 (February 4 – June 28) and 2025 (February 9 – June 7).

From the AP5 imagery, fSCA remained ~90% until mid-April in 2024, while 2025 exhibited an earlier melt, beginning around April 1. This trend continued through the melt season, with the 2025 curve consistently leading 2024. 2025 reached melt completion (~10% FSCA) in mid-May, with 2024 doing the same around June 1. This indicates an earlier melt onset and completion by nearly two weeks between the years. The APB imagery showed a more consistent melt onset, with both 2024 and 2025 showing initial decline around April 1. Despite this, the completion of melt occurred on June 1 for 2025 and June 15 in 2024, a similar difference to AP5's findings.

Overall, while only AP5 showed a clearly earlier onset of melt in 2025, both sites exhibited earlier snow-free conditions by nearly two weeks in 2025 compared to 2024. Additionally, both 2024 fSCA timeseries exhibit fluctuations in the late season, which

appears to have extended snow presence at APB and contributed to the offset in melt completion.

FSCA and Heterogeneity

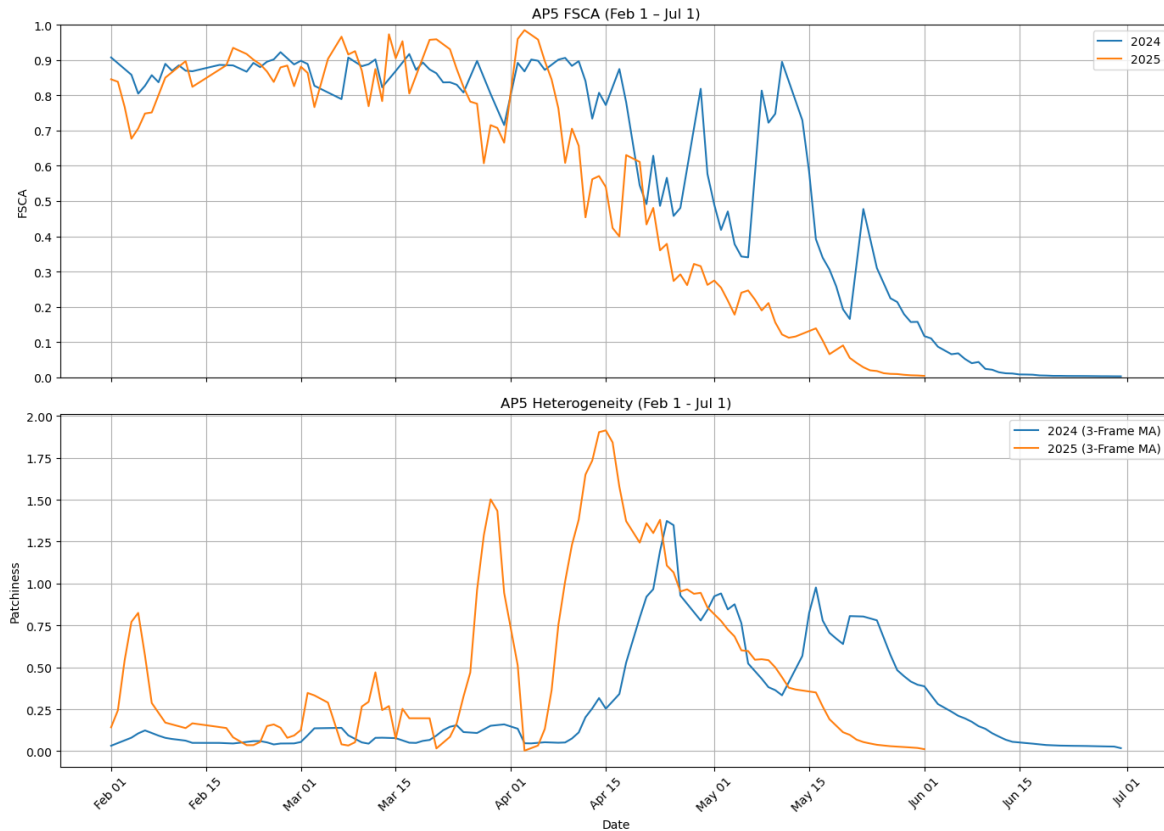


Figure 9. *AP5 FSCA and Heterogeneity Index (Feb 1 – Jul 1)*

For AP5, heterogeneity remained low through mid-April in 2024, consistent with the consistently high FSCA. Significant increase began in mid-April and peaked at ~1.4 around April 25. 2024 experienced a secondary rise in mid-May, consistent with FSCA fluctuations. In 2025, patchiness experienced fluctuations in February and March, in line with periodic decreases in FSCA, before sharply increasing in early April. The index reached a maximum of ~1.9 on April 15, the highest observed from either year. After their peaks, both curves steadily, closely following fSCA.

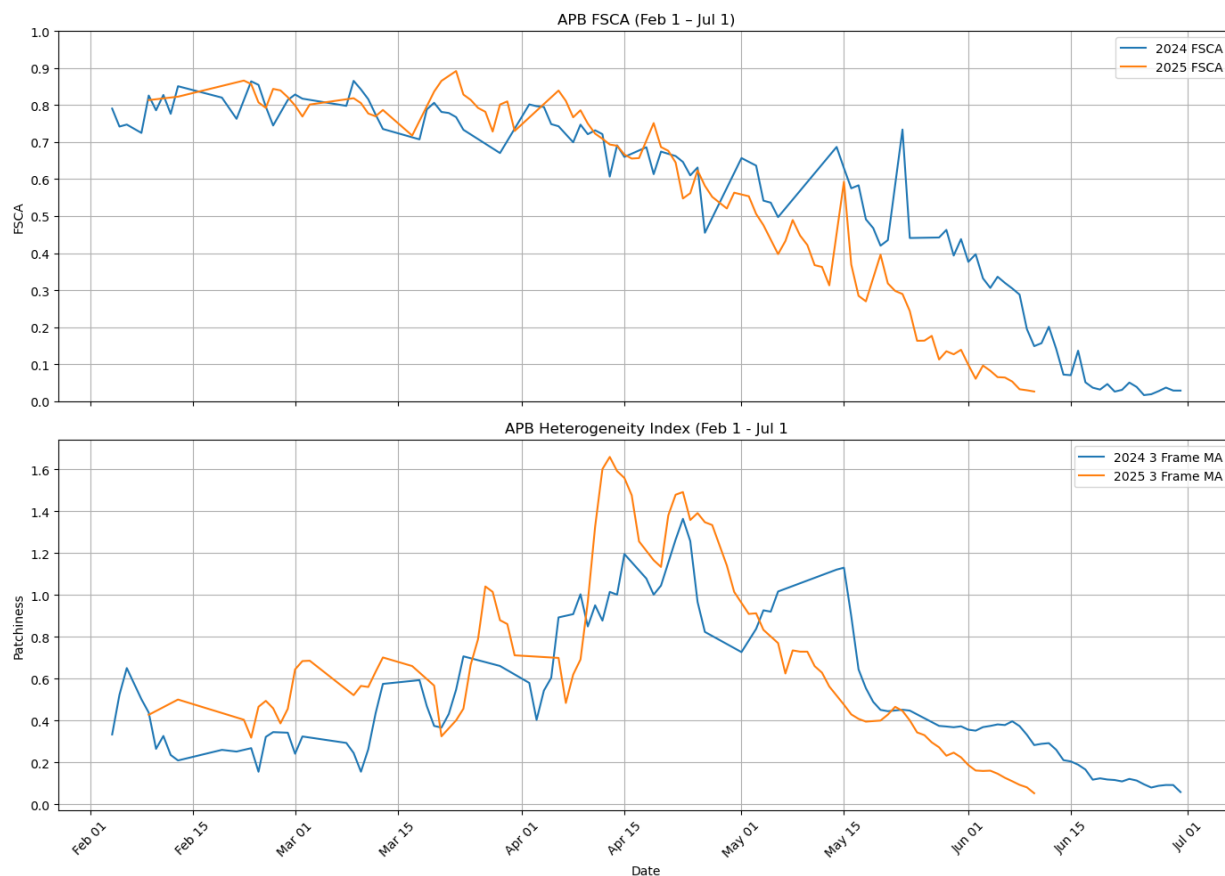


Figure 10. *APB fSCA and Heterogeneity Index (Feb 1 – Jul 1)*

For APB, the trends were similar but less extreme. 2025 peaked on April 12 at ~1.6, with 2024 occurring later and lower with ~1.3 on April 25. Similar to AP5, the 2024 curve experienced a secondary rise around mid-May. After their peaks, both curves steadily, closely following fSCA.

For both sites, the index was consistent with adjusting to rapid changes in fSCA, namely storms. 2025 displayed earlier heterogeneity changes at a similar offset to fSCA, as well as greater peak heterogeneity values. These peaks typically came when fSCA was in the 50-70% range. This suggests that not only was the melt earlier, but also patchier.

FSCA and Greenup

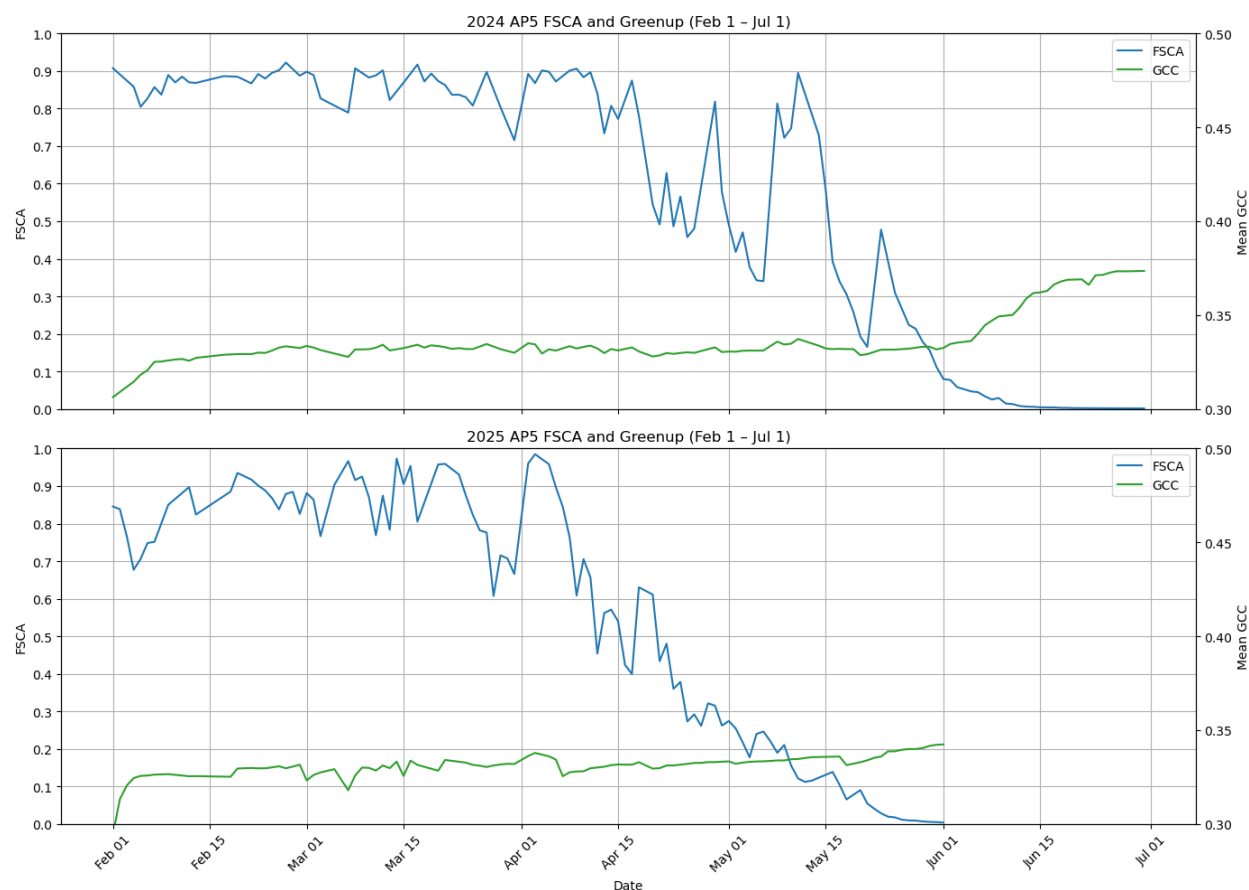


Figure 11. AP5 FSCA and Greenup (Feb 1 – Jul 1)

For AP5, mean GCC remained relatively flat at ~0.33 from February through April in both years. In 2024, greenup began around June 1, shortly after fSCA fell to 10%. The same was not seen in 2025, which had no significant increase up to June 1, despite having reached 10% fSCA well before then. The cause of this deviation is likely a result of differences in the region being analyzed, which is explored further in the Discussion section.

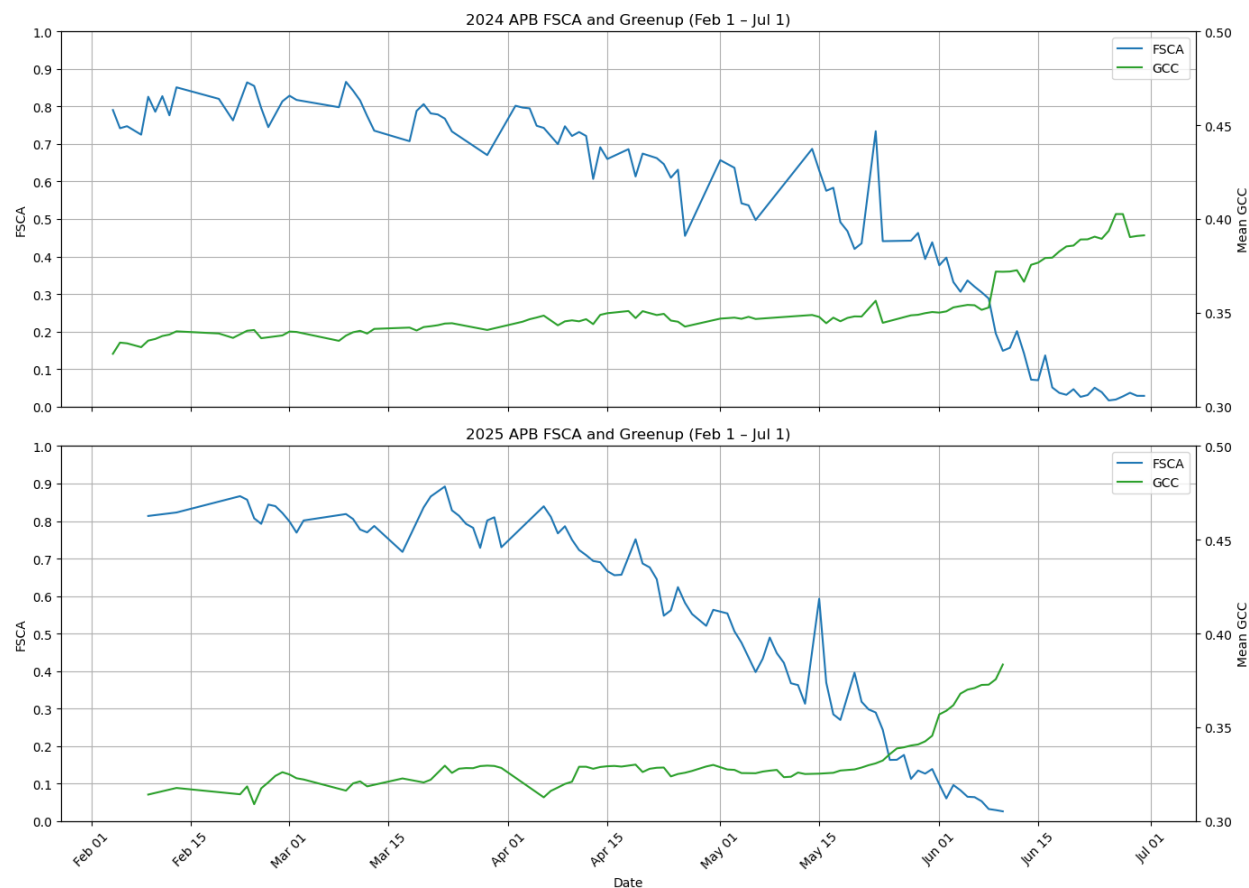


Figure 12. APB FSCA and Greenup (Feb 1 – Jul 1)

APB showed a more expected greenup sequence. In 2024, greenup began to rise around June 1, with fSCA at 40%. In 2025, this increase occurred significantly earlier around May 15, with fSCA down to 30%. On June 7, when the 2025 curve ends, both GCC averages were ~.38. Similar to AP5, there is a discrepancy in the regions being analyzed, which will be acknowledged in the Discussion section.

The results from both years and sites show greenup generally following fSCA's decline, with earlier melt in 2025 often leading to earlier increases in GCC averages.

Discussion

Snowmelt Timing and Heterogeneity

The imagery analysis revealed significant differences in the timing of snowmelt across both sites, with 2025 fSCA consistently exhibiting melt completion two weeks earlier than 2024. Interestingly, only AP5 demonstrated a proportionately early melt onset, while APB showed nearly identically melt out starts in both years. This difference may be explained by site-specific characteristics, such as aspect, elevation, or slope grade, which may affect melt onset conditions regardless of interannual variables. Additionally, the 2024 melt season was marked by significant fSCA fluctuations during the late spring. These temporary fSCA pullbacks are attributed to several late-season snowstorms consistent with daily weather records from the Gothic weather station (*Daily Data, 2024*).

The heterogeneity index displayed earlier and higher values in 2025 for both sites, which may be explained by seasonally variation in solar energy. Earlier melt outs, like 2025, occur while the sun is lower in the sky and days are shorter. Lundquist et al. (2006) demonstrates that these low sun angles result in greater shading and a more uneven distribution of solar energy. As a result, 2025 likely experienced spatial variations in melt energy, and therefore greater heterogeneity. Conversely, 2024's later melt received a more uniform solar input that promoted a more uniform melt pattern.

Altogether, the comparison between the 2024 and 2025 melt seasons serves as a compelling example of the effects of an earlier melt onset compared to an average year. The results from this project suggest that earlier melt onset can promote greater snow heterogeneity, as seen in 2025. Meanwhile, the late-season storms of 2024 show the effects of smaller weather events potentially impacting snow distribution and heterogeneity.

Greenup

The vegetation greenup consistently followed the retreat of snow cover across both sites, reinforcing that greenup is dependent on snow disappearance. In all but one case, GCC values only began rising after snow cover had receded. The exception case is discussed below. As expected, this created temporal offsets nearly identical to the those seen between 2024 and 2025 in FSCA and heterogeneity. This suggests that earlier melts allow for earlier greenup.

AP5's 2025 greenup is the exception to this, as it never sees a noticeable increase in mean GCC. One likely factor is the frame composition. Due to unintentional camera movement, the region of interest for the greenup analysis capture less vegetation than 2024 (Fig. 13). A similar issue occurred in the analysis for APB, but the difference is more apparent in the AP5 greenup (Fig. 11) where a delayed greenup signal was observed despite earlier snowmelt.



Figure 13. *Comparison of frames used for APB GCC 2024 and 2025 analyses. The area within the red box is included in the 2024 analysis, but out of frame in the 2025 imagery.*

Additionally, there is a difference in the mean GCC observed between the two sites, which can be explained by a difference in vegetation types. AP5's greenup peaked at ~ 0.37 and consists of mostly aspen trees, while APB contains grassy vegetation and reached upwards of 0.4.

Future Work - Orthorectification

While the current analysis effectively tracks snowmelt and greenup dynamics based on the imagery gathered, it assumes uniform spatial scaling throughout the image. However, because the imagery has an oblique field of view, pixels in the background (further away) represent significantly more surface area than those in the foreground. This introduces distortion when quantifying snow cover and vegetative changes. To address this, future work will involve orthorectifying the imagery at each site by aligning the pixels to real world coordinates. This will enable the area-based metrics used to reflect spatially accurate measurements.

Conclusion

This study demonstrates the utility that pixel analysis of color imagery has for understanding spring snowpack distribution and its hydrologic implications. By developing and applying a heterogeneity index and integrating a greenup analysis as a proxy for evapotranspiration, we highlight the effects of earlier snowmelt on snow cover heterogeneity, and potentially streamflow efficiency. As the western U.S. faces uncertain water futures and inconsistencies between snowpack and runoff, improving our ability to predict how snowmelt translates to runoff is vital. This project contributes to this goal by advancing methods to quantify the spatial and temporal components of melt patterns. With future efforts such as orthorectification and streamflow modeling, these findings offer a new lens to help researchers and water managers better assess the fate of snowmelt and its contribution to streamflow in a changing climate.

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