LINKING SNOWPITS TO SNOW MECHANICS WITH AN EXTENSIBLE ALGORITHMIC FRAMEWORK

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ABSTRACT: Mechanical models of avalanche release require mechanical properties of snow, such as Young's modulus, E, and Poisson's ratio, ν, that are seldom measured directly in snowpits. Snowpit observations are widely collected, standardized, and central to avalanche practice, but the methods available to translate them into mechanical parameters remain limited. Multiple published parameterizations can estimate mechanical properties from common field observations, but they differ in input requirements, validity domains, and resulting uncertainty, and their chained combinations have not been systematically enumerated or compared. We present SnowPyt-MechParams, an extensible graph-based framework that encodes a selection of parameterizations and their dependencies as a directed acyclic graph, enumerates unique calculation pathways, executes those pathways on slab objects derived from snowpit observations, and propagates input measurement uncertainty through chained calculations. As an example implementation, we use SnowPylot to parse SnowPilot CAAML files from the 2015–2025 water years, yielding 50,278 snowpits, 371,429 layers, and 14,776 slabs constructed from propagating Extended Column Test results. We compare the number of valid pathways and the coverage across those pathways to ascertain the slope-parallel component of slab weight per unit area, W_{shear}, with and without elasticity parameters E and ν for each layer in the slab. Within the implemented framework, there are four valid pathways for W_{shear}, and the highest coverage pathway succeeds for 5,470 slabs (37.0 %). The mechanically richer target with elasticity yields 32 valid pathways, of which the highest coverage pathways succeed for only 687 slabs (4.6 %). These results surface a gap between modern mechanical model requirements and currently available methods for estimating mechanical parameters from snowpit observations.

KEYWORDS: snow mechanics; snowpits; avalanche release; SnowPilot; parameterization; uncertainty

1. INTRODUCTION

Recent developments in mechanical models of snow, including the Material Point Method (MPM) and the Weak Layer Anticrack Nucleation Model (WEAC), have made substantial progress in representing processes involved in dry slab avalanche release (Weißgraeber and Rosendahl 2023; Siron et al. 2023; Bergfeld et al. 2023). These models require more mechanical information than legacy approaches such as the Roch Stability Criterion (Roch 1965), including inputs that are rarely measured directly in the field, such as the Young's modulus and Poisson's ratio of snowpack layers.

In practice, snowpits remain a primary methodology for gathering field observations of snowpack structure and layer properties in a context that is usable for forecasters, guides, patrollers, and recreational users (LaChapelle 1980; Greene et al. 2022; CAA Technical Committee 2024).

This creates a translation problem between practical observations and theoretical model inputs. Snowpit observations may include the hand hardness, grain form, and grain size of a snowpit layer, while a mechanical model may require density, Young's modulus, and Poisson's ratio. To bridge this gap, researchers often rely on chains of published parameterizations. For example, density may be measured directly or estimated from hand hardness and grain form (Geldsetzer and Jamieson 2000; Kim and Jamieson 2014); Young's modulus may then be estimated from density; slab stiffness may then be calculated from the elastic properties and thicknesses of all slab layers (Weißgraeber and Rosendahl 2023). Multiple methods can often reach the same target, and each method has different input requirements, validity domains, and uncertainty.

The goal of this work is to make those chains explicit and comparable. We present an open-source Python framework and algorithm that enumerates

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calculation pathways from snowpit observations to mechanical properties of snow. The framework does not choose the “best” method. Instead, it asks practical questions that matter before a model is applied: What observations are required? What and how many snowpits or slabs can support the calculation? Where does the pathway fail? How much uncertainty is carried through the chain? And when several pathways succeed, how different are the answers? At dataset scale, these questions reveal where existing parameterizations are insufficient and provide a structure for evaluating future methods.

2. SNOWPIT DATA AND CALCULATION PATHWAYS

SnowPilot (snowpilot.org) is a free, open-source application for recording, visualizing, and storing snowpit observations (Chabot et al. 2004; Chabot et al. 2016). The broader database contains more than 65,000 snowpits contributed by recreationists and professionals worldwide, and is particularly popular among avalanche professionals in North America.

For this analysis, we exported SnowPilot CAAML XML files (CAA Technical Committee 2024) from the 2015–2025 water years. This dataset contains 50,278 snowpits and 371,429 layers. The XML files were parsed with SnowPylot, a Python library we developed to import SnowPilot exports and organize them into structured Python objects (Connelly et al. 2026).

To define slabs at population scale, we selected snowpits with Extended Column Test (ECT) results with propagation (Simenhois and Birkeland 2006; Toft et al. 2024). For each propagating ECT, the slab was defined as the layers above the recorded failure layer, yielding 14,776 slabs. The input observations used in the example include layer thickness, hand hardness, primary grain form, grain size, direct density when it can be matched exactly to a snow-profile layer, and pit slope angle. These observations are common enough to support a large comparison, but they are not complete for every layer or pit. That incompleteness is important: a method that is theoretically useful may have low practical coverage if it depends on observations that are rarely recorded or fall outside the validity domain of established parameterizations.

In our framework, we represent snowpit observations, layer mechanical parameters, and slab properties as nodes in a directed acyclic graph (DAG; Fig. 1). Unnamed edges represent data flow by direct transfer, and named edges represent the transformation of data by a named, established parameterization. At a parameter node (square), incoming edges represent ways to calculate the parameter represented by the node. At a merge node (diamond), all incoming edges are required inputs to outgoing method edges. Traversing the graph backward from a target parameter enumerates the distinct calculation pathways and the observations each pathway requires.

Density is a simple target that illustrates how the graph and algorithm enumerate all possible ways a parameter can be calculated from snowpit field observations utilizing the included parameterizations (Fig. 2). Starting at the target parameter, density, the algorithm traverses the graph backward and considers each incoming edge as an alternative method. One branch reaches measured density directly, so the only required input is a matched density observation. The other branches pass through merge nodes, where the algorithm collects all required inputs before continuing: the Geldsetzer method (Geldsetzer and Jamieson 2000) and Kim Table 2 (Kim and Jamieson 2014) require both hand hardness and grain form, while Kim Table 6 from the same study requires hand hardness, grain form, and grain size. The algorithm therefore returns four distinct pathways to the same density target, each with a specific method choice and a specific set of required snowpit observations.

Uncertainty is represented with the Python `uncertainties` package (Lebigot 2010). Because SnowPilot stores nominal observations but not observation uncertainty, we assign measurement uncertainties from published studies and field experience: direct density $\pm 10\,\%$ (Conger and McClung 2009; Proksch et al. 2016), slope angle $\pm 2°$, hand hardness $\pm$ two subclasses, grain size ± 0.5 mm, and layer thickness $\pm 5\,\%$. The results reported here propagate measurement uncertainty only; method-specific regression uncertainty is supported by the framework but was not included in this example comparison.

3. EXAMPLE MECHANICAL TARGETS

The example implementation focuses on slab-side quantities needed by mechanical models of avalanche release. We compare pathways to ascertain the slope-parallel component of slab weight per unit area, W_{shear}, with and without elasticity parameters. The simpler target requires slab weight alone. For a slab with layers $n = 1, \ldots, N$, total weight per unit area is

$$W = \sum_{n=1}^{N} \rho_n g h_n, \tag{1}$$

where ρ_n is layer density, h_n is layer thickness, and g is gravitational acceleration. The shear component is

$$W_{\text{shear}} = W \sin \psi, \tag{2}$$

where ψ is the slope angle. This target requires density and thickness for every slab layer, as well as slope angle.

A mechanically richer target also requires elasticity parameters for each slab layer: Young's modulus (E), and Poisson's ratio, (ν). These parameters can be used to calculate slab stiffness terms such as extensional stiffness, bending stiffness, bending-extension coupling, and shear stiffness (Rosendahl and Weißgraeber 2020; Weißgraeber and Rosendahl 2023). We implemented representative parameterizations for density, Young's modulus, and Poisson's ratio from the literature (Geldsetzer and Jamieson 2000; Kim and Jamieson 2014; Köchle and Schneebeli 2014; Wautier et al. 2015; Srivastava et al. 2016; Bergfeld et al. 2023; Schöttner et al. 2026). The intent is not to provide an exhaustive review, but to show how an extensible framework can compare chained combinations of methods on the same slabs.

In the implemented graph, four pathways can calculate W_{shear}. Adding E and ν creates 32 pathways because each density method can be paired with multiple Young's-modulus and Poisson's-ratio methods. A slab-level pathway succeeds only if every layer in the slab satisfies all required observations and method-validity checks.

4. RESULTS

The four W_{shear} pathways have different practical coverage (Fig. 3). The highest-coverage pathway uses the Kim Table 2 density relationship (Kim and Jamieson 2014) and succeeds for 5,470 of 14,776 slabs (37.0 %). The Geldsetzer pathway (Geldsetzer and Jamieson 2000) succeeds for 4,187 slabs (28.3 %), Kim Table 6 (Kim and Jamieson 2014) succeeds for 697 slabs (4.7 %), and direct matched density observations succeed for 109 slabs (0.7 %). The direct-density result is low because only 2.8 % of SnowPilot layers have density observations that match the snow-profile layer boundaries exactly.

Adding elasticity parameters sharply reduces coverage. The best pathways that calculate W_{shear} with E and ν succeed for 687 slabs (4.6 %). The highest-coverage pathways use Kim Table 2 density (Kim and Jamieson 2014), either Wautier (Wautier et al. 2015) or Schöttner (Schöttner et al. 2026) for Young's modulus, and Köchle (Köchle and Schneebeli 2014) for Poisson's ratio. Similar pathways using Geldsetzer density (Geldsetzer and Jamieson 2000) succeed for 684 slabs (4.6 %). Pathways that use Srivastava (Srivastava et al. 2016) for Poisson's ratio have lower coverage because they impose an additional density threshold.

The same framework can compare output magnitude and uncertainty when multiple pathways succeed for the same slab. For bending stiffness, D_{11}, the 16 highest-coverage pathways share 317 slabs with finite positive values. Across those common slabs, the median propagated relative measurement uncertainty is 78 % (IQR: 56–85 %). The median within-slab spread ratio, defined as the maximum pathway estimate divided by the minimum pathway estimate, is 32. This means that even when several methods are all valid for the same slab, the selected chain of parameterizations can strongly affect the calculated mechanical property.

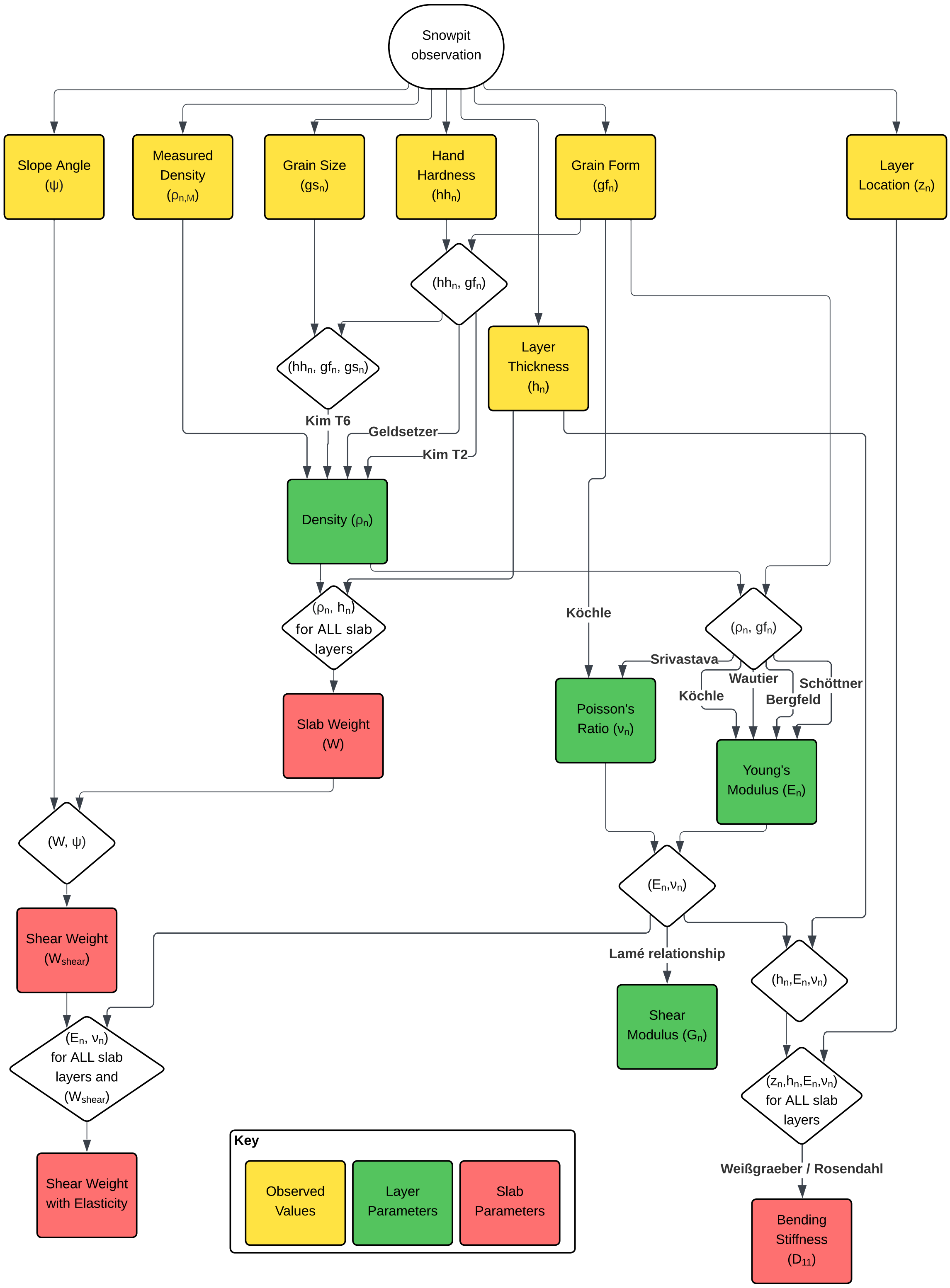

Figure 1: The full parameter DAG used to enumerate calculation pathways. Yellow rectangles are observed snowpit values, green rectangles are layer-level parameters, and red rectangles are slab-level parameters. Diamond nodes collect multiple required inputs for one method. The graph makes method comparison explicit: each pathway is a particular set of input observations and parameterization choices used to reach a target parameter.

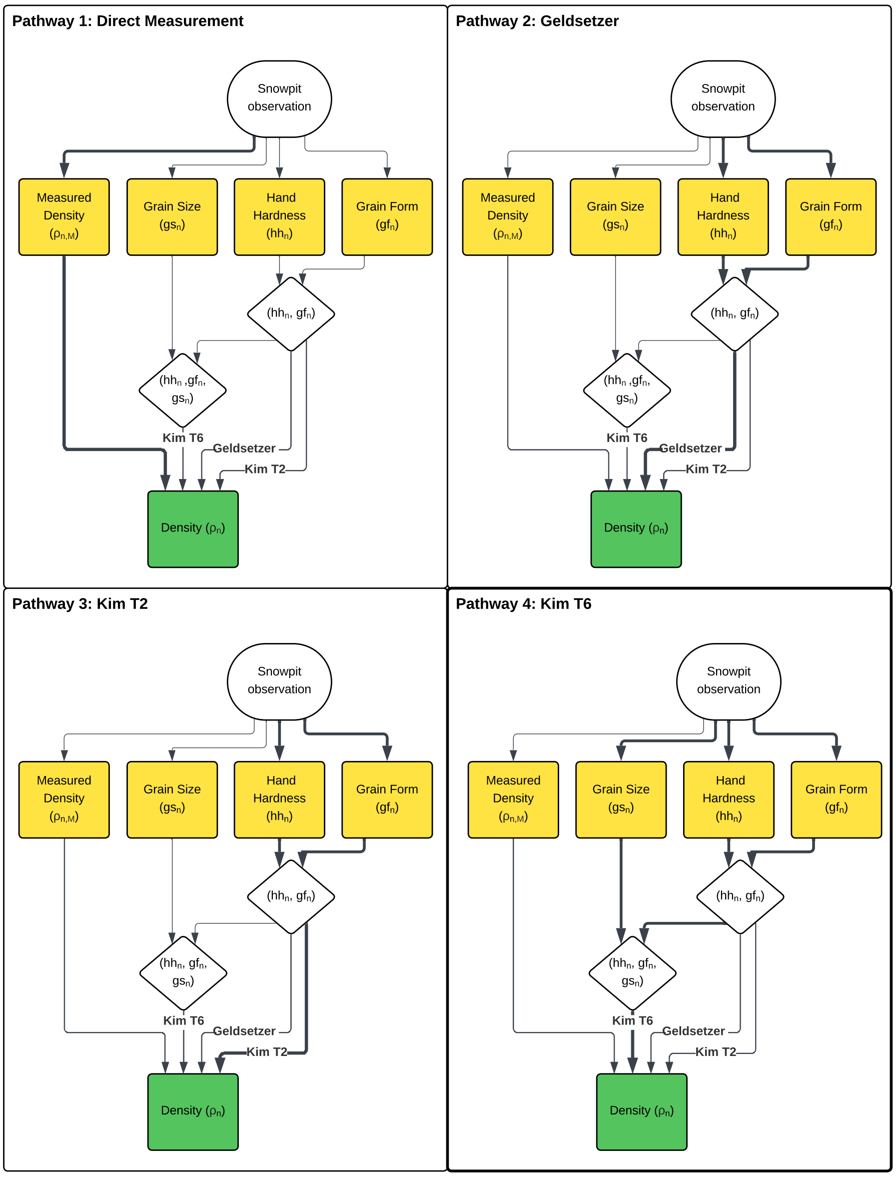

Figure 2: Density provides a simple example of pathway enumeration. It can be taken from a matched direct measurement or estimated from published relationships using hand hardness, grain form, and in one case grain size (Geldsetzer and Jamieson 2000; Kim and Jamieson 2014). Downstream slab calculations inherit the chosen density method and its input requirements.

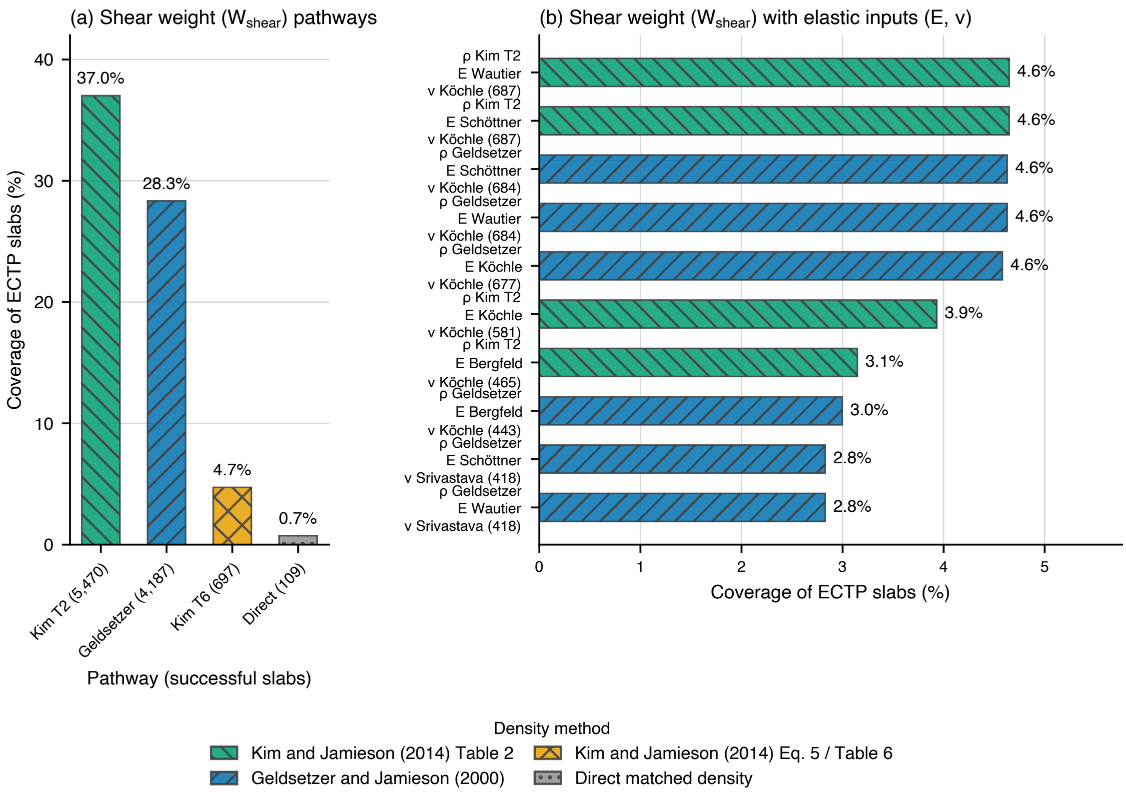

Figure 3: Coverage of slab-property pathways evaluated on 14,776 ECTP slabs. The highest-coverage W_{shear} pathway succeeds for 37.0 % of slabs. The highest-coverage pathway that also requires E and ν succeeds for 4.6 % of slabs.

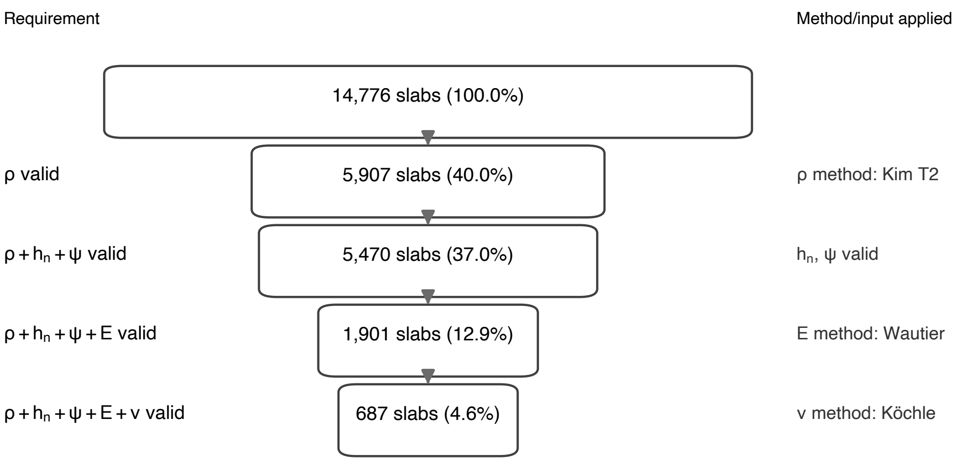

Figure 4: Stepwise attrition along one of the highest-coverage pathways that calculates W_{shear} with E and ν: Kim Table 2 density (Kim and Jamieson 2014), Wautier Young's modulus (Wautier et al. 2015), and Köchle Poisson's ratio (Köchle and Schneebeli 2014). The final target succeeds only when the required observations and method domains are satisfied for every layer in the slab.

5. DISCUSSION

The coverage results show an input-assembly bottleneck rather than a failure of any single parameterization. Shear weight is comparatively accessible because it requires density, layer thickness, and slope angle. Adding E and ν requires longer chains. Each added link creates another chance for a missing observation, unsupported grain form, or out-of-range density to stop the pathway. At slab scale, the requirement applies to every layer, so one unsupported layer can cause the whole slab calculation to fail.

This bottleneck highlights a methods gap between standardized snowpit observations and the inputs required by modern mechanical models. Snowpit observations are a strong foundation for linking field practice and research because they are popular and structured. The limiting step is the current set of methods available to translate snowpit field measurements into mechanical parameters with known coverage, validity, and uncertainty.

For practitioners, this gives a concrete way to think about the value of field observations. Density measurements are powerful when they are present and matched to layers, but they are sparse in practice, as evidenced by the SnowPilot dataset. Grain form and hand hardness are much more common, so density parameterizations based on those observations have higher coverage, but also higher uncertainty. In addition, any results from mechanical models or simulations that are based on input snowpit observation data should be interpreted with caution and judgment.

For snow scientists and model developers, the framework provides a method-comparison tool. Instead of applying one preferred chain by hand, the graph enumerates the alternatives, records their input requirements, executes them consistently, and reports success, failure, uncertainty, and output range. This makes it possible to separate several questions that are often blended together: whether a method is physically appropriate, whether its inputs are commonly observed, whether its validity domain matches real snowpit data, and whether its output agrees with other valid methods. New parameterizations can be added to the graph and compared against existing methods on the same slabs to test whether they improve coverage, reduce uncertainty, or expand validity.

For technology developers, the framework provides a compelling illustration of the value for directly observing mechanical properties of snow. For example, if Young's modulus is measured directly, then calculation chain is shortened and uncertainty is reduced. We encourage continued development of instruments such as the blade hardness gauge (Borstad and McClung 2011), snow micropenetrometer (Schneebeli and Johnson 1998), and SnowSoundPen (Pietro et al. 2024). This instrumentation development should be paired with mechanistic interpretation of their measurements for direct observation of mechanical properties.

The current implementation has important limits. SnowPilot is a community-sourced database, so observer skill, observation purpose, and record completeness vary. The direct-density matching rule is intentionally strict and likely underestimates usable density information, but it keeps the analysis reproducible. The slab definition is based on ECTP failure depth and is a convenient population-scale test case, not a complete description of every avalanche problem. The mechanical calculations assume effective isotropic, linearly elastic layer properties and perfect bonding between layers, although real snow is anisotropic, rate dependent, and inelastic.

6. CONCLUSIONS

SnowPyt-MechParams provides a reproducible way to enumerate, execute, and compare calculation pathways from standardized snowpit observations to mechanical properties of snow.

The example SnowPilot analysis shows two main results. First, mechanically richer targets come with a coverage cost: the best W_{shear} pathway succeeds for 37.0 % of ECTP slabs, while the best pathway that also requires elasticity parameters E and ν succeeds for 4.6 %. Second, method choices matter even when pathways succeed: for D_{11}, the median max/min pathway ratio is 32 and median propagated relative measurement uncertainty is 78 %.

These results do not imply that mechanical models are impractical. Rather, they show that the bridge from field observations to model inputs must be evaluated explicitly. Current methods for estimating mechanical parameters from common snowpit observations are not yet sufficient to fully leverage standardized snowpit datasets in the latest mechanical models, motivating future research on new parameterizations, direct mechanical measurements for validation, and expanded validity domains. By comparing methods by coverage, uncertainty, and output range, SnowPyt-MechParams gives researchers a reproducible way to evaluate those improvements and communicate the limits and opportunities of mechanically based snowpack interpretation.

More details on the framework and analysis of this work can be found as a pre-print (Connelly et al. 2026).

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