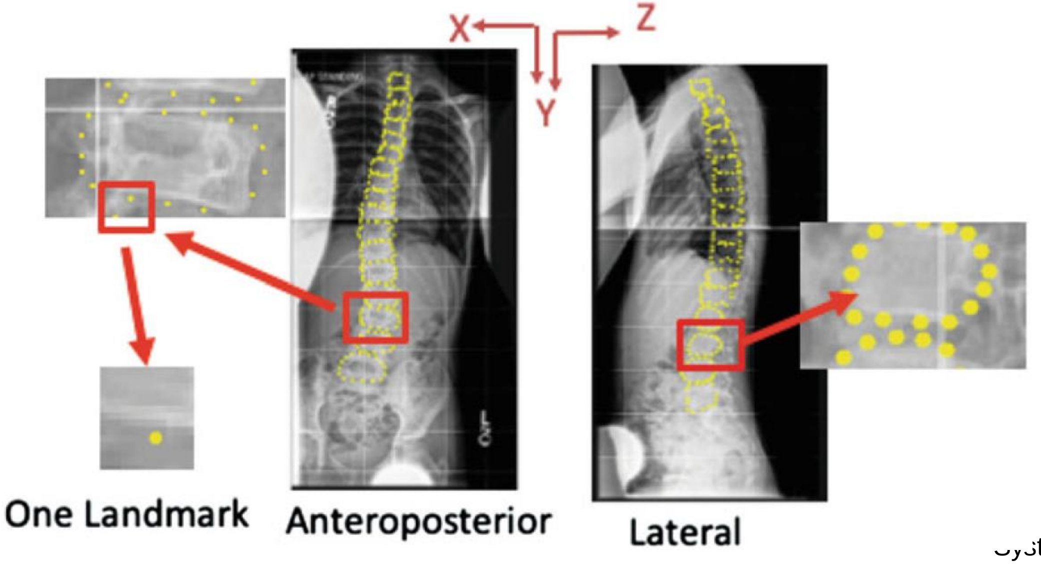
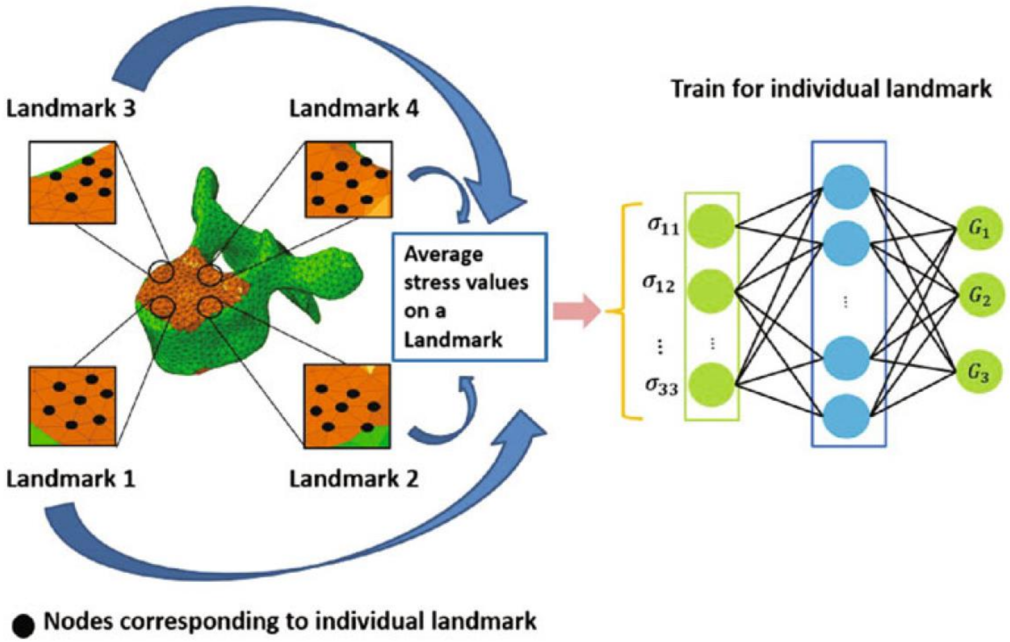
Spine Growth Prediction

- adolescent idiopathic scoliosis (AIS) 청소년기 특발성 측만증
  - A pure physics-based analysis of the spine and this condition are currently not possible because of the complicated nature of the spinal materials and the slow progress of the condition
  - assess through a series of “snapshots” taken through X-rays
  - do not provide much detail related to the interaction between the vertebrae
- Step 1: Multimodal data generation and collection
  - X-ray imaging taken from the front and the side in intervals specified by the doctor
  - These two image projections establish the position of the spine at a given instant in time and allow for further measurements of the progression of AIS

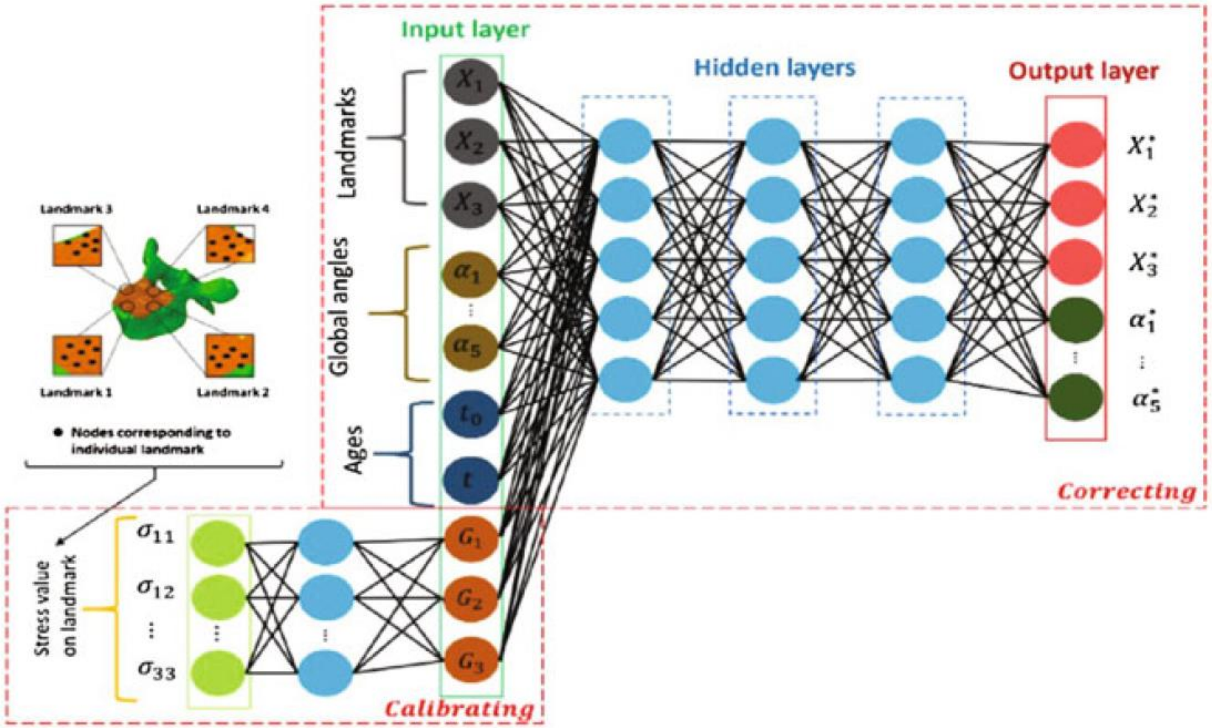
- Steps 2, 3 and 4: Extraction of mechanistic features, knowledge-driven dimension reduction, reduced-order surrogate models (blurry)
  - compute the location of the vertebra of interest in three dimensions
  - use of the snake method to create landmarks outlining each vertebra
  - establish a three-dimensional bounding box for each vertebra
  - 3D reference ATLAS model is deformed using the generated landmarks of the X-ray image
  - The data for the 3D reduced order model were then used to refine the dimension of a 3D detailed ATLAS model of the vertebrae

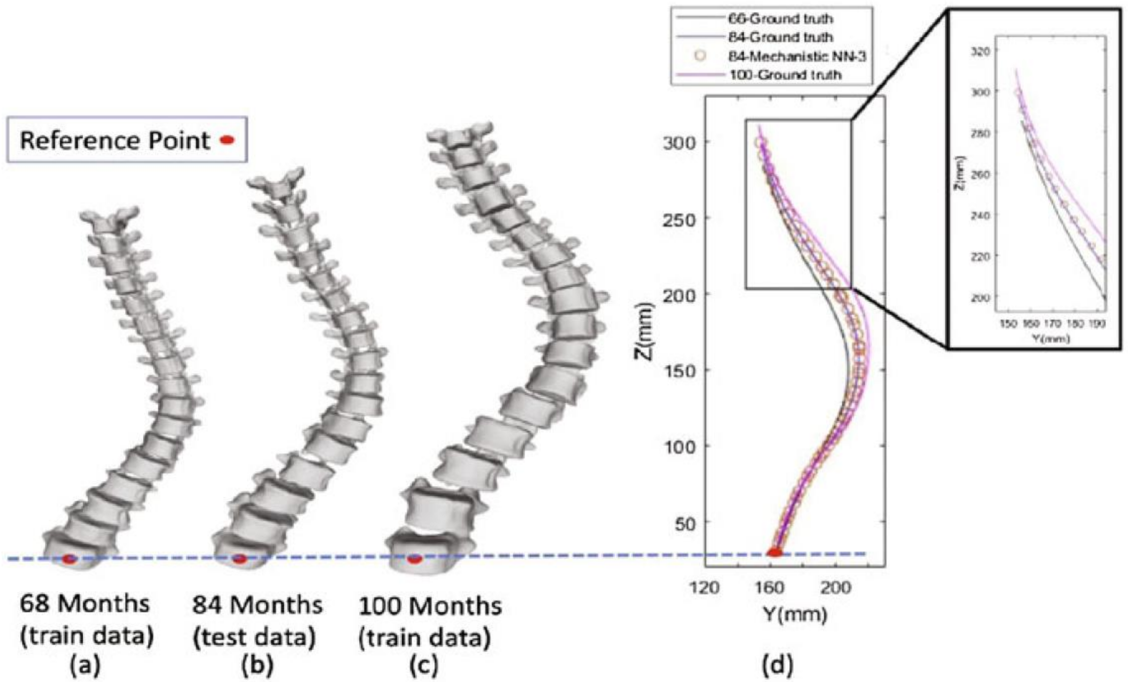


- Step 5: Deep learning for regression and classification
  - create a finite element model of the spine
  - compute the contact pressure at key landmark locations of the surface of the vertebrae
  - The predicted contact pressures from the finite element model were combined with the clinical measurements of spine growth in a neural network
  - This allowed for a more patient-specific prediction of vertebrae growth



- Step 6: System and design
  - prognosis patient-specific spinal growth and deformity
  - input: data collected and generated based on the X-ray imaging
  - output: predicted stress data at landmark locations



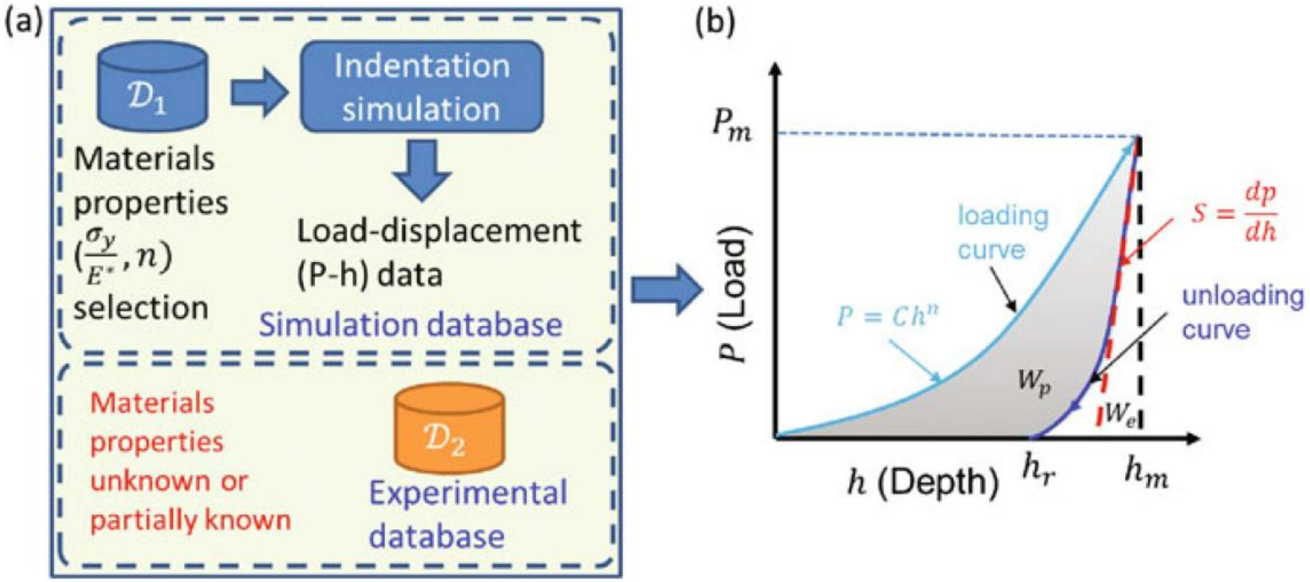


Indentation Analysis for Materials Property Prediction

- Indentation: useful technique to extract mechanical properties of materials
  - low-cost semi or nondestructive testing procedure
  - less time-consuming than tensile testing
  - providing important materials properties such as hardness and elastic modulus
- indenter of known shape (e.g., spherical, conical, etc.), size, and materials is penetrated through the workpiece
- load-displacement data (P-h curve) is recorded for both loading and unloading of the indenter through the testing workpiece
  - Important materials physics such as plasticity, yielding
  - signature of the materials localized properties
  - For metal and alloys, dislocations are generated and propagated

- Indentation test --> hardness data for a material at the location
  - Hardness: localized property that varies from point to point of the materials
  - related to other mechanical properties of the materials such as yield strength, elastic properties, and hardening parameters.
- Predicting materials properties from the localized hardness data: inverse problem of the indentation
  - AM: relation between the localized hardness and yield strength can be established for an AM build Ti-64 alloy parts
- Objective: establish the relation of the experimental low resolution materials property data with indentation testing data (hardness) first and then transfer it for simulation data using transfer learning to find the materials property (yield strength and hardening parameters) from an inverse problem

- Step 1: Multimodal data generation and collection
  - Nanoindentation data for AM built part for different processing conditions
  - S3067 processing conditions having 144 indentation tests data: experimental data set (high-fidelity testing data)
  - 70 numerical indentation simulations (input: material property)
- Step 2: Mechanistic features extraction



Mechanistic features	SI unit
Curvature, C	Pa (N/m^2)
Slope of unloading curve, S	N/m
Maximum load, P_m	N
Maximum depth, h_m	m
Plastic to total work ratio, $\frac{W_p}{W_t}$	–
Hardness, H	Pa
Reduced modulus, E^*	Pa
Yield strength, σ_y	Pa
Hardening parameter, n	–

- Steps 3 and 4: Knowledge-driven dimension reduction and reduced order surrogate models
  - six important nondimensional groups

$$C, P_m, h_m, h_c, A_c, S, H, E^*$$

$$p = Ch^n$$

$$H = P_m / A_c$$

$$h_c = h - \frac{\varepsilon P_m}{S}$$

$$E^* = \frac{S}{2\beta}\sqrt{\frac{\pi}{24.56}}$$

$$\frac{1}{E^*} = \frac{1-{\nu_s}^2}{E_s} + \frac{1-{\nu_i}^2}{E_i}$$

$$\frac{C}{E^*} = \Pi_1\left(\frac{\sigma_y}{E^*}, n\right)$$

$$\frac{S}{E^* h_m} = \Pi_2\left(\frac{\sigma_y}{E^*}, n\right)$$

$$\frac{W_p}{W_t} = \Pi_3\left(\frac{\sigma_y}{E^*}, n\right)$$

$$\frac{H}{E^*} = \Pi_4\left(\frac{\sigma_y}{E^*}, n\right)$$

$$\left(\frac{\sigma_y}{E^*}, n\right) = f\left(\frac{C}{E^*}, \frac{S}{E^* h_m}, \frac{W_p}{W_t}, \frac{H}{E^*}\right)$$

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Scaling, dimensional analysis, and indentation measurements

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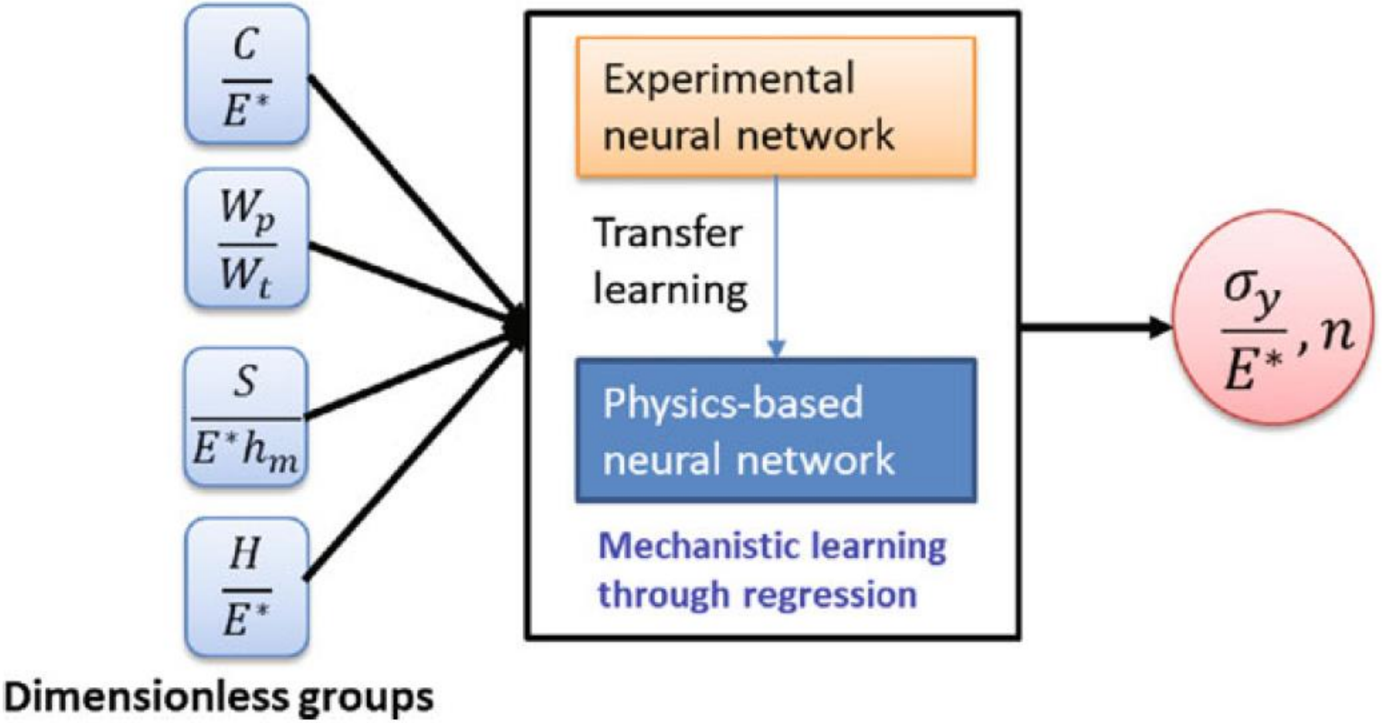
Abstract

We provide an overview of the basic concepts of scaling and dimensional analysis, followed by a review of some of the recent work on applying these concepts to modeling instrumented indentation measurements. Specifically, we examine conical and pyramidal indentation in elastic–plastic solids with power-law work-hardening, in power-law creep solids, and in linear viscoelastic materials. We show that the scaling approach to indentation modeling provides new insights into several basic questions in instrumented indentation, including, what information is contained in the indentation load–displacement curves? How does hardness depend on the mechanical properties and indenter geometry? What are the factors determining piling-up and sinking-in of surface profiles around indents? Can stress–strain relationships be obtained from indentation load–displacement curves? How to measure time dependent mechanical properties from indentation? How to detect or confirm indentation size effects? The scaling approach also helps organize knowledge and provides a framework for bridging micro- and macro-scales. We hope that this review will accomplish two purposes: (1) introducing the basic concepts of scaling and dimensional analysis to materials scientists and engineers, and (2) providing a better understanding of instrumented indentation measurements.

Keywords: Scaling; Analysis; Indentation

- Step 5: Deep learning for regression
  - experimental neural network
    - two hidden layers with 50 neurons eacl
    - “ReLU” type activation function
    - Training, testing, validation: 70%, 20%, for the dataset
    - R2 = 0.70
  - Physics-based neural network
    - two additional hidden layers having 20 neurons each
    - R2 = 0.74



- Step 6: System and design for new materials system
  - sample size: 360 μm by 360 μm
  - indenter is indented every 30 μm apart

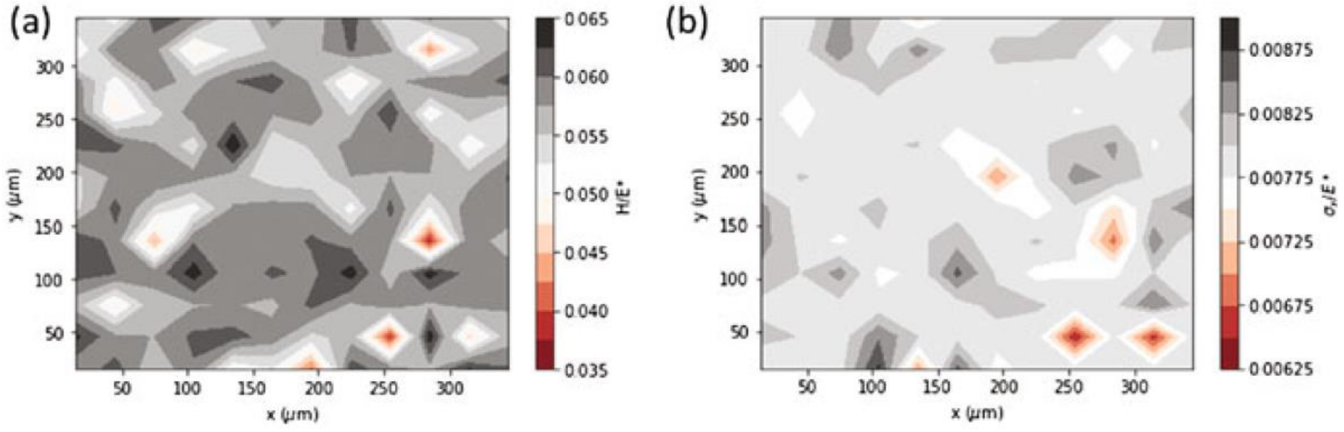
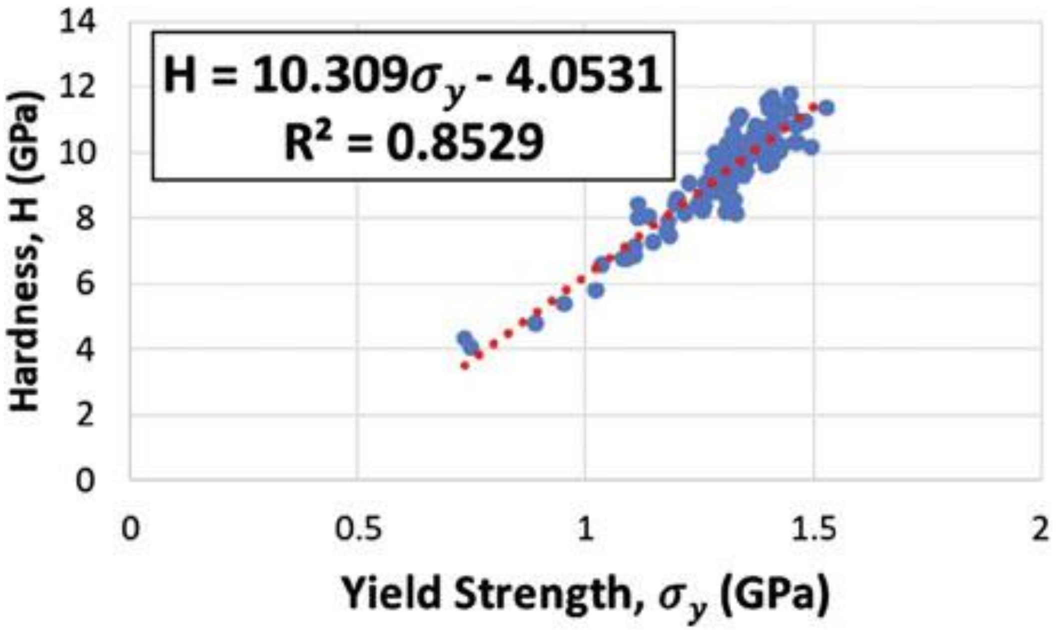


Fig. 7.28 (**a**) Nondimensional hardness distribution over the AM sample surface, (**b**) MDS predicted localized yield strength mapping

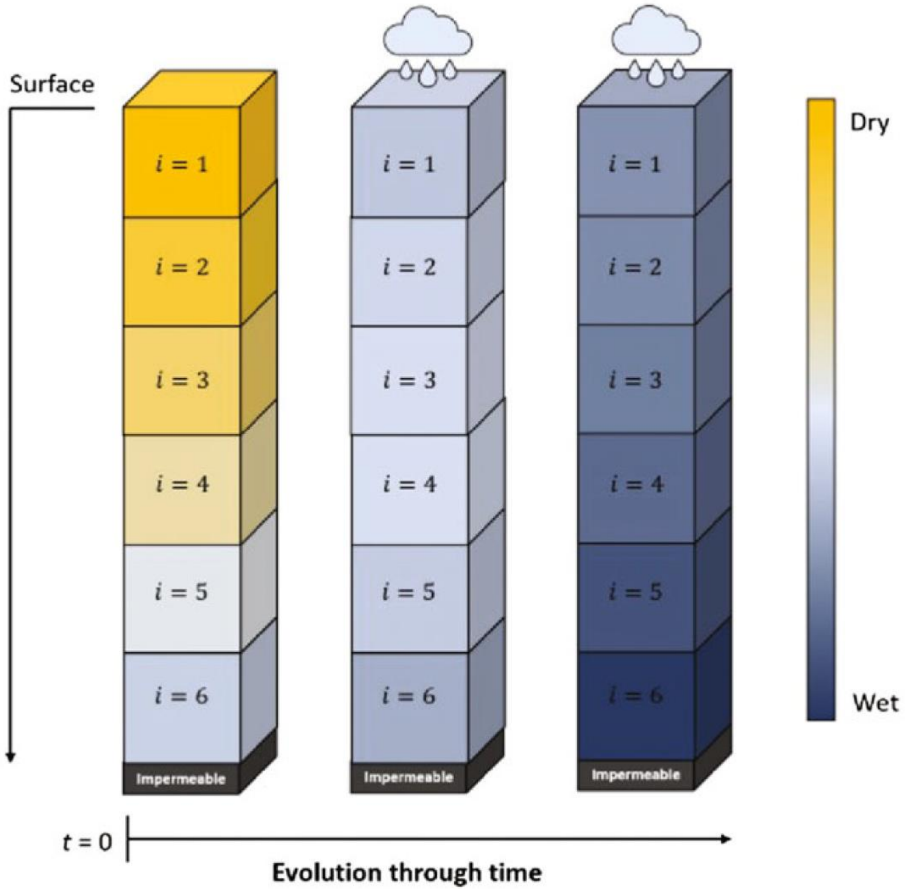


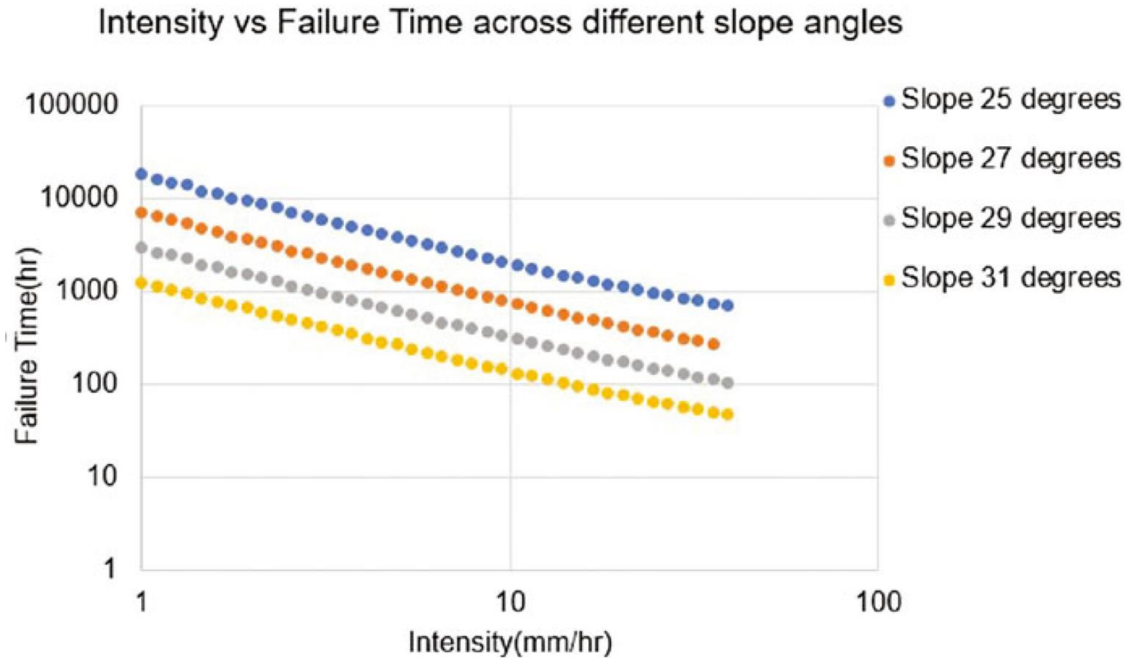
Early Warning of Rainfall Induced Landslides

- A landslide occurs when the soil and rocks on a hillside give way and a large section of the hillside suddenly moves down the hill
  - Cost of landslides damage in the United States exceeds $1 billion per year
  - Factors: soil type, rainfall, and slope inclination
  - One key parameter is soil moisture due to rain and storms, which inspires the construction of precipitation intensity-duration thresholds for shallow, rainfall induced landslides
  - Thresholds developed from limited historical databases of rainwater infiltration have large variability in landslide occurrence times
- Landslide Early Warning Systems (LEWS)
  - analyze the interplay of numerous key parameters and conditions for landslide prediction

- Step 1: Multimodal data generation and collection
  - Many historical landslide databases do not include all these parameters
    - Failure time: time it takes for a landslide to occur
    - Rainfall intensity: amount of water incident on a soil per unit time (mm/h)
    - Soil cohesion: measure of the force that holds together soil particles.
    - Soil porosity: percentage of air or spaces between particles of soil in a given sample
    - Soil density: dry weight of the soil divided by its volume
    - Initial moisture conditions: difference in weight of the soil dry and weight of the soil when moist
    - Slope angle: angle measured from a horizontal plane to a point on the land
  - Simulation
    - physical evaluation of a factor of safety threshold to determine when the landslide occurs based on the moisture content throughout the soil column
    - water infiltration events with different parameters to compute the time for the slope to become unstable
    - Data were extracted from the database for these soil parameters

– combining historical data with data generated from water infiltration simulations



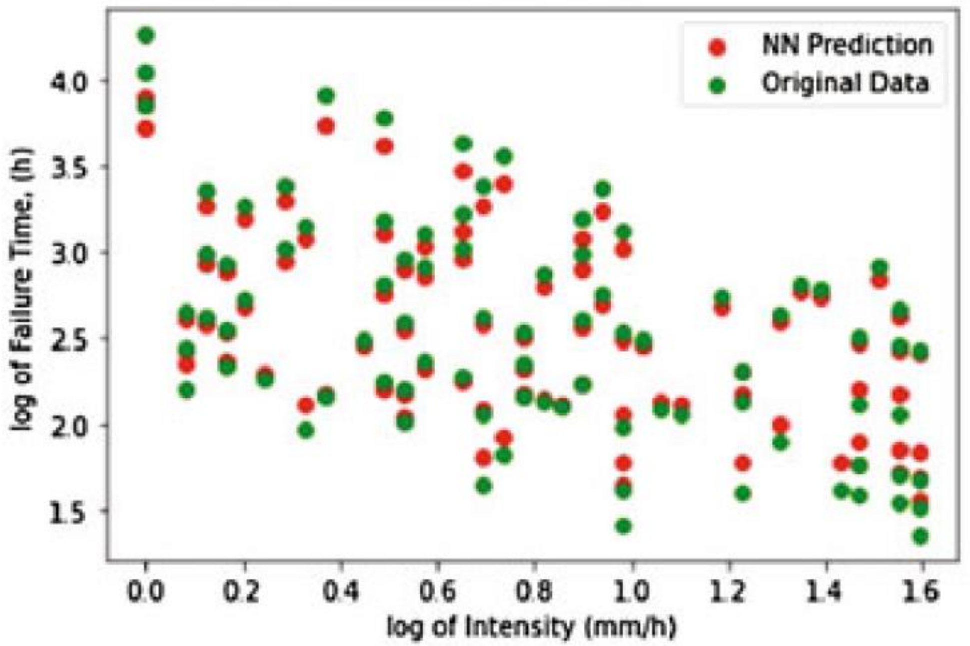


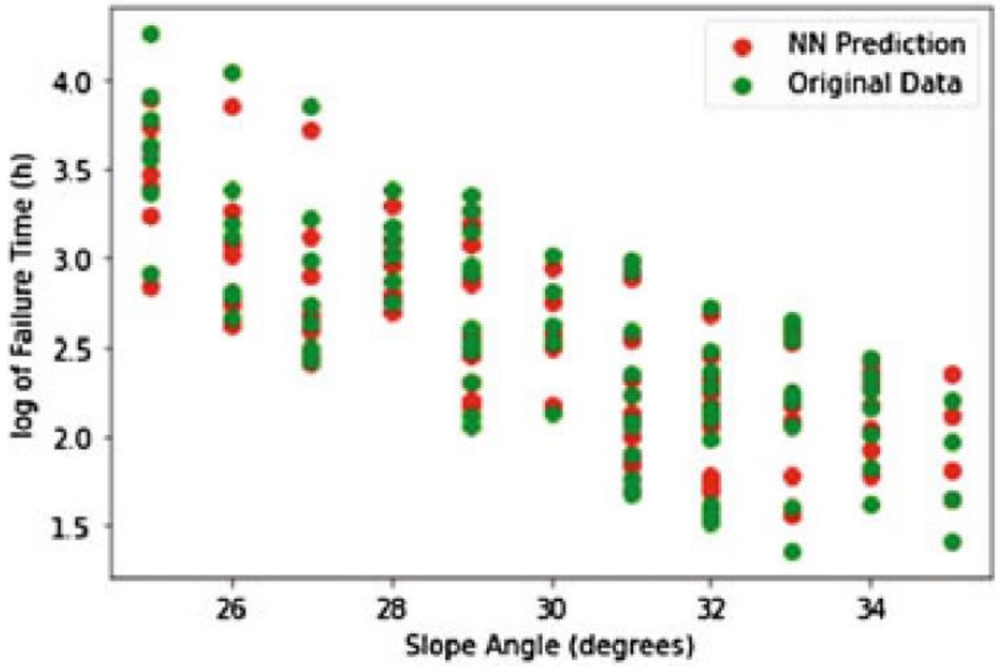
- Step 2: Extraction of mechanistic features
  - input: rainfall intensity and slope angle (external conditions are more easily measured compared to specific soil parameters)
  - output: failure time

Parameters	Units	Range
Failure time	h	1–20,000
Rainfall intensity	mm/h	1–40
Slope angle	°	25–35
Soil cohesion	°	37.24
Porosity	%	71.5
Soil density	g/cm^3	8.7
Initial soil moisture content	kPa	3.57

- Steps 3, 4: knowledge-driven dimension reduction and reduced order surrogate models
  - rainfall intensity and slope angles are varied for data generation and database preparation, which reduces the problem dimension significantly

- Step 5: Deep learning for regression
  - k-fold cross-validation
  - MAE: 0.04~0.05, R2=0.96





- Step 6: System and design for intensity-duration thresholds
  - trained neural network can then be used to compute the rainfall intensity-duration thresholds that indicate landslide risk
  - coastal and mountainous areas of California, which are some of the areas most susceptible to landslides in the United States