Development of geochemical paleoclimate proxies and pedotransfer functions for paleosols

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The great interest in paleosol bulk geochemistry has driven two primary directions of research: 1) estimation of paleoclimate conditions, chiefly mean annual precipitation (MAP) and mean annual temperature (MAT), and 2) estimation of colloidal soil properties such as pH, base saturation, CEC, etc. that relate to soil ecosystem function. Initial paleoclimate proxies were developed based on relatively small and somewhat biased soil data sets in which MAP was limited to 200-1600 mm yr⁻¹ and MAT was limited to 2-22 °C [1]. Our research group recently developed a more widely applicable paleoclimate model (PPM_{1.0}) using 600+ B horizons of North American soils forming under spanning greater ranges of MAP (130-6900 mm yr⁻¹) and MAT (0-27 °C), but this increased range has come at a cost in terms of increased error estimates for MAP [2]. Whereas estimations of MAP for paleosols appear generally reliable, many available MAT proxies underestimate MAT based on paleolatitudinal reconstructions and paleobotanical proxies; these are paleosols lacking sufficient time of pedogenesis to achieve equilibrium with climate due to geomorphic instability within paleoenvironments. Another area of development is pedotransfer functions useful for estimating colloidal properties. Although well-established for one type of soil (Vertisols: heavy clay soils with a high shrink-swell potential) and their paleosol equivalents [3], only soil pH has thus far been shown amenable to a universal soil approach [4]. Rather than continuing with traditional regression-based approaches, promising new avenues include regression trees and machine learning to more thoroughly interrogate soil geochemical data bases [5].

[1] Sheldon et al. (2002) *J. Geol.* **110**, 687-696. [2] Stinchcomb et al. (2016) *Am. J. Sci.* **316**, 746-777. [3] Nordt and Driese (2010) *Am. J. Sci.* **310**, 37-64. [4] Lukens et al. (2018) *J. Geol.* **126**, 427-449. [5] Lukens et al. (in review) *Am. J. Sci.*