# Progress and Challenges in Studying Regional Permafrost in the Tibetan Plateau Using Satellite Remote Sensing and Models

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Recent climate change has induced widespread soil thawing and permafrost degradation in the Tibetan Plateau. Significant advances have been made in better characterizing Tibetan Plateau soil freeze/thaw dynamics, and their interaction with local-scale ecohydrological processes. However, factors such as sparse networks of *in-situ* sites and short observational period still limit our understanding of the Tibetan Plateau permafrost. Satellite-based optical and infrared remote sensing can provide information on land surface conditions at high spatial resolution, allowing for better representation of spatial heterogeneity in the Tibetan Plateau and further infer the related permafrost states. Being able to operate at "all-weather" conditions, microwave remote sensing has been widely used to retrieve surface soil moisture, freeze/thaw state, and surface deformation, that are critical to understand the Tibetan Plateau permafrost state and changes. However, coarse resolution (>10 km) of current passive microwave sensors can add large uncertainties to the above retrievals in the Tibetan Plateau area with high topographic relief. In addition, current microwave remote sensing methods are limited to detections in the upper soil layer within a few centimetres. On the other hand, algorithms that can link surface properties and soil freeze/thaw indices to permafrost properties at regional scale still need improvements. For example, most methods using InSAR (interferometric synthetic aperture radar) derived surface deformation to estimate active layer thickness either ignore the effects of vertical variability of soil water content and soil properties, or use site-specific soil moisture profiles. This can introduce non-negligible errors when upscaled to the broader Tibetan Plateau area. Integrating satellite remote sensing retrievals with process models will allow for more accurate representation of Tibetan Plateau permafrost conditions. However, such applications are still limiting due to a number of factors, including large uncertainties in current satellite products in the Tibetan Plateau area, and mismatch between model input data needs and information provided by current satellite sensors. Novel approaches to combine diverse datasets with models through model initialization, parameterization and data assimilation are needed to address the

above challenges. Finally, we call for expansion of local-scale observational network, to obtain more information on deep soil temperature and moisture, soil organic carbon content, and ground ice content.

**Keywords: process models, satellite remote sensing, freeze/thaw, permafrost, Tibetan plateau**

# INTRODUCTION

The Tibetan Plateau has an average elevation of 4,000 m and encompasses an area of approximately $2.5 \times 10^6$ km² (**Figure 1**). It is the home to ~100,000 km² of glaciers (Yao et al., 2012) and possesses the largest alpine permafrost area in the world (Ran et al., 2018; Cheng et al., 2019). The Tibetan Plateau is also the headwater of many major Asian rivers including the Yangtze, Yellow, Mekong, Indus, and Ganges (Immerzeel et al., 2010). Due to its vast domain and high elevation, the Tibetan Plateau is extremely sensitive to climate change and has a profound influence on the regional climate (Duan and Wu, 2005).

Long-term *in-situ* surface meteorology measurements show that the Tibetan Plateau has been experiencing a significant warming trend since 1960s, with an average rate of 0.3–0.4°C per decade, which exceeds the global average during the same period (Chen et al., 2015a). Previous studies further indicated such warming trend is elevation-dependent. Specifically, the warming rate increases with elevation for lower altitude regions (<~4,500–5,000 m) and this phenomenon is more obvious during autumn and winter (Yan and Liu, 2014), while

this warming trend is absent or lower at higher elevations (>~5,000 m) based on satellite-based temperature datasets (Guo et al., 2019; Pepin et al., 2019). Other changes include slight increases in precipitation, wind speed weakening, solar radiation declining and mixed trends of relative humidity (Yang et al., 2014; Bibi et al., 2018). These changes can have significant impact on regional water and energy balance, and cause non-negligible changes in the cryosphere, including glacier retreat, soil warming and permafrost degradation.

Frozen ground occupies the most area of the Tibetan Plateau (**Figure 1**), with approximately 40% coverage of permafrost and 55% coverage of seasonally frozen ground (Zou et al., 2017). Since the 1970s, several *in-situ* observation networks have been established to monitor the thermal state of Tibetan Plateau frozen ground (Yang et al., 2010). These *in-situ* soil temperature records have demonstrated substantial changes occurred in Tibetan Plateau frozen ground including permafrost degradation over the past few decades. For example, the *in-situ* observations in the Beiluhe region indicated that the active layer thickness has increased at a rate of ~4.26 cm yr$^{-1}$ from 2002 to 2012 while the permafrost
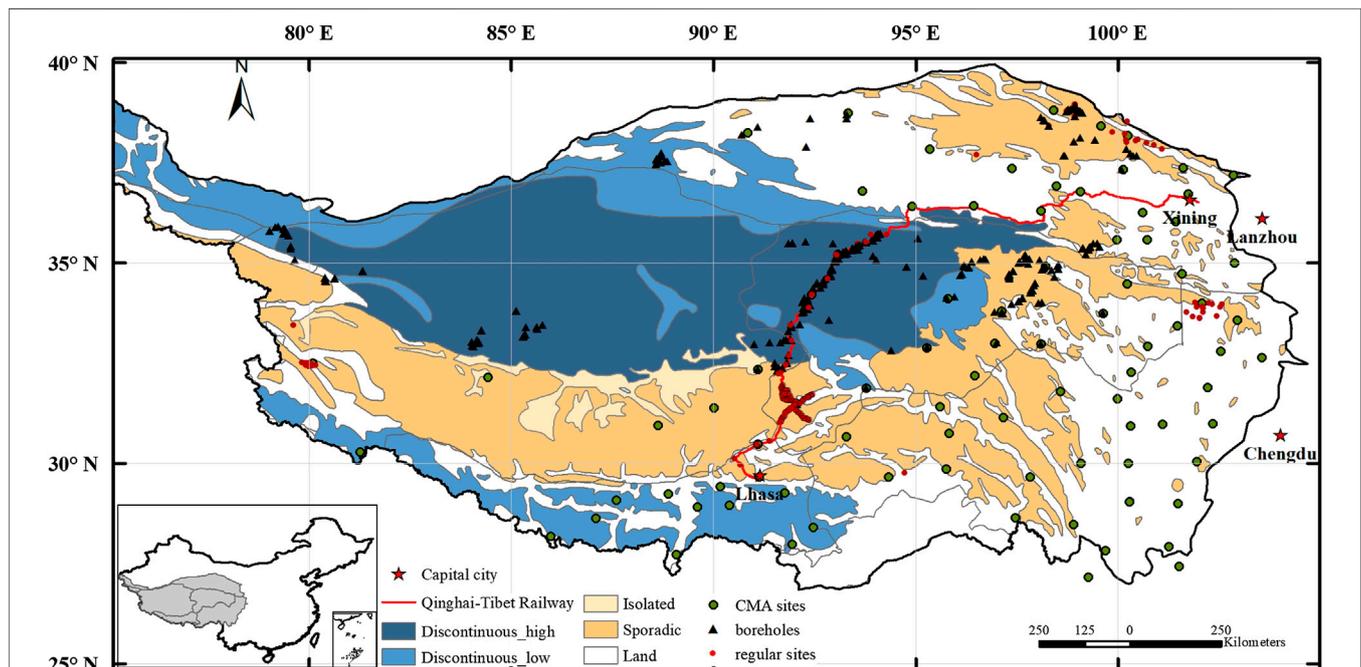


**FIGURE 1 |** The distribution of permafrost and *in-situ* observations over the Tibetan Plateau region. The permafrost classification is based on the international permafrost association permafrost map (Brown et al., 1997), and the "high" and "low" in the legend refer to the ice content of permafrost. Green dots represent meteorological stations from China Meteorological Administration, black triangles refer to the borehole sites with deeper soil temperature measurements from previous studies (Wu and Zhang, 2008; Luo et al., 2012; Cao et al., 2019), and red dots are regular observation sites with soil temperature observations within a depth of a few meters (data source including Yang et al., 2013a; Cao et al., 2019; Zheng et al., 2020).

temperatures at 10 m depth have increased by ~0.14°C during the same period (Wu et al., 2015). In the inner Tibetan plateau, maximum frozen depth decreased at a rate of 0.71 cm yr$^{-1}$ during the period 1967–1997 (Zhao et al., 2004), and reduction in the maximum frozen depth has accelerated since 2000 (Peng et al., 2017). Previous study also revealed that a distinct talik layer separating the permafrost from overlying active layer has already formed along the Qinghai-Tibet Highway (Jin et al., 2008).

Previous studies based on the *in-situ* observations provided detailed assessments of *permafrost thermal state at local scales*. However, extrapolating site-level observations across the Tibetan Plateau is likely to entail large uncertainties, due to the sparse *in-situ* stations, shallow observation depth at most sites, inconsistency in the measurement methods and data gaps. Most *in-situ* observations and boreholes (up to 10 m) were established along the Qinghai-Tibet Railway/Highway to meet the engineering demand (Wu and Zhang, 2008; Jin et al., 2011; Wu et al., 2020), while most of the meteorological stations from China Meteorological Administration are located in the seasonally frozen ground of the central or eastern Tibetan Plateau (**Figure 1**).There are limited *in-situ* observations in the western Tibetan Plateau, with only a few boreholes located in A-erh-chin Mountain, Gaize and west Kunlun (Zou et al., 2017). The limited number of *in-situ* sites poses great challenges for a comprehensive, regional-scale assessment of the Tibetan Plateau permafrost thermal state. For example, there are large discrepancies among the current Tibetan Plateau permafrost coverage maps (Zou et al., 2017; Wu et al., 2018; Zheng et al., 2020), and it is difficult to accurately evaluate these maps due to the different compilation approaches and insufficient *in-situ* observations (Cao et al., 2019).

Satellite or airborne remote sensing can provide information on environmental conditions and freeze/thaw state related to underlying permafrost properties with improved sensitivity to subsurface soil properties (Jorgenson and Grosse, 2016), which can provide critical constraints on assessing regional permafrost vulnerability. With a wide range of satellite and airborne observations available from existing and upcoming missions, remote sensing data are increasingly becoming an essential element for regional permafrost monitoring (NRC, 2014). However, current satellite remote sensing systems cannot provide information on deeper (>~10 cm) soils; therefore, an integration of remote sensing data with process-based models are needed to obtain information on permafrost properties and dynamics. This review summarizes recent progress and challenges using multi-source satellite remote sensing data and process-based models to improve regional permafrost monitoring across Tibetan Plateau. Airborne remote sensing also plays an important role in regional permafrost studies (Miller et al., 2019). For example, the airborne electromagnetic method has shown a great potential in mapping Alaskan permafrost (Minsley et al., 2012; Rey et al., 2019). However, there is very limited airborne experiment in the Tibetan Plateau; therefore, we only briefly discuss its application in regional permafrost studies, which mainly occur in other permafrost areas (*Discussion*).

The paper is structured as follows: we first discuss the unique characteristics of Tibetan Plateau permafrost environment (*Environmental Controls on Tibetan Plateau Permafrost Distribution and Soil Freeze/Thaw Dynamics*), and then summarize the recent advances in regional Tibetan Plateau permafrost studies using various remote sensing technologies, and through combination of remote sensing with modeling approaches (*Regional Monitoring Approaches and Associated Challenges*). We also discuss the unique challenges in Tibetan Plateau permafrost monitoring, the potential of geophysical measurements and other methods to characterize subsurface variability and spatial heterogeneity in permafrost areas (*Discussion*). We conclude by addressing research priorities and future studies needed to accurately simulate the evolution of Tibetan Plateau permafrost and eco-hydrology (*Research Priorities and Recommendations*).

# Environmental Controls on Tibetan Plateau Permafrost Distribution and Soil Freeze/Thaw Dynamics

The Tibetan Plateau is characterized by relatively thin and warm permafrost with low ice content, potentially more vulnerable to ongoing and future warming due to the unique environmental conditions, arid climate, high elevation and steep geothermal gradient (Wang and French, 1995; Yang et al., 2010; Zhao et al., 2010; Cheng et al., 2019; Zhao et al., 2020). Therefore, an improved understanding of permafrost sensitivity to environmental conditions in the Tibetan Plateau region is essential for effectively monitoring potential changes and vulnerability of Tibetan Plateau permafrost (**Figure 2**).

Permafrost distribution in the Tibetan Plateau is controlled by the high elevation and complex topography, and has characteristics different from permafrost in other regions (Wang and French, 1995). Topographic factors such as elevation affect regional climate through the effects on precipitation, temperature lapse rates and solar radiation loading (Gruber et al., 2017). Therefore, topography can affect soil freeze/thaw dynamics by altering the land surface temperature and the surface energy budget. Field investigations show that the lower limit of permafrost in the Yellow River region is ~4,400 a.s.l., while seasonally frozen ground occurs at lower elevations such as major river valleys (Luo et al., 2012). Other topographic factors, such as aspect and slope, also influence permafrost distribution. Due to different solar radiation loading on different slope and aspect, the lower limit of Tibetan Plateau permafrost on the north slope is usually lower than that on the south slope with more sunny conditions (Cheng and Wu, 2007). *In-situ* data from the central Tibetan Plateau show that the average frost depth was much deeper on north facing slopes than on south facing slopes, and varied considerably with elevation on both slopes (Ma et al., 2015).

Soil conditions also have a significant influence on permafrost thermal state. Soil texture is one of the major factors determining soil thermal conductivity, heat capacity, and hydraulic conductivity (Chen et al., 2012; Yi et al., 2018a). For example, gravel soils have a larger thermal conductivity and can result in a

**FIGURE 2 |** Interaction among different environmental factors and soil freeze/thaw (F/T) dynamics in the Tibetan Plateau region. Solid and dash arrows indicate the influences and feedbacks respectively. ALT and MFD represent active layer thickness (defined for permafrost area) and maximum frozen depth (defined for seasonally frozen ground) respectively.
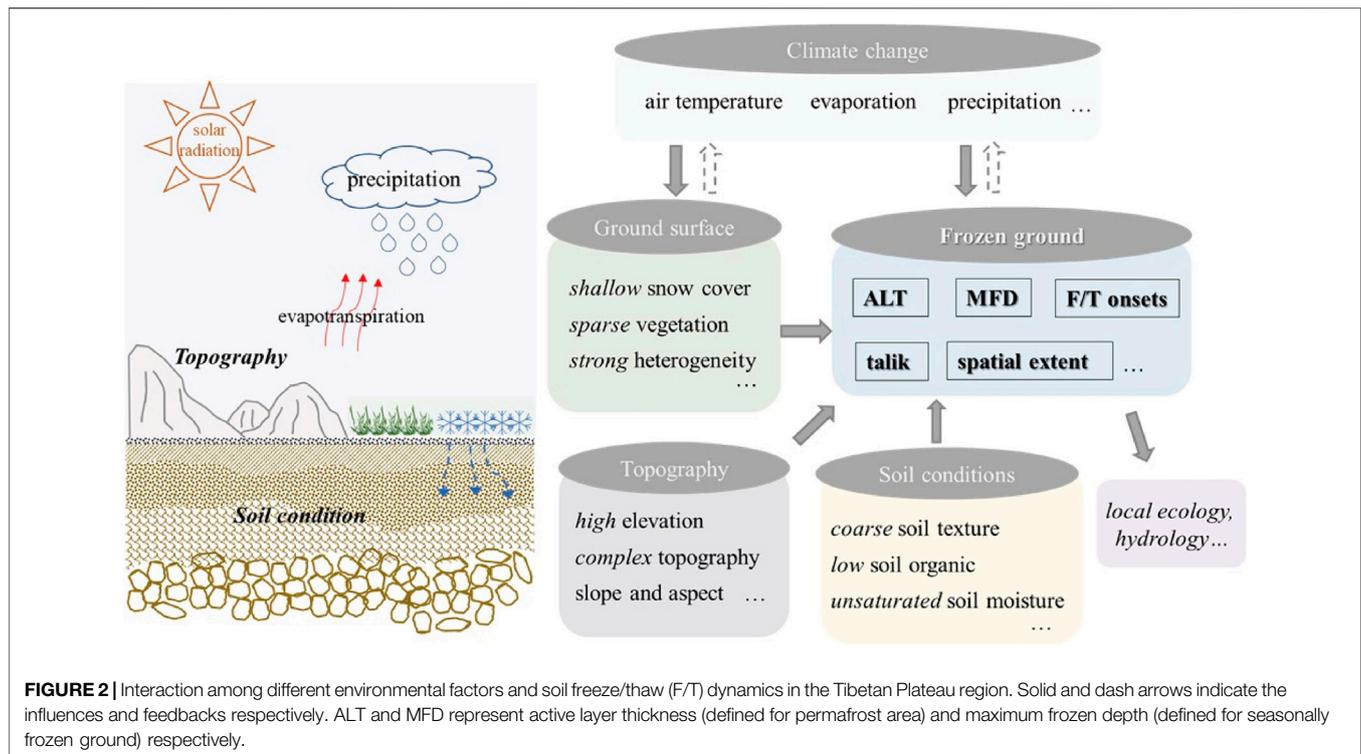
rapid response of soil temperatures to climate change. The existence of gravels also tends to reduce the soil water holding capacity and enhance hydraulic conductivity and drainage (Pan et al., 2017). As the consequence of slow soil-forming processes and strong erosion, gravel soils are widespread in the Tibetan Plateau and has distinct physical properties from agricultural soils (Arocena et al., 2012; Yi et al., 2018a). In addition, given that bedrock has quite different hydrological and thermal properties from upper soil layers, soil depth (or the depth to bedrock) also has significant influence on soil freeze/thaw dynamics especially for deep soils. Soil moisture content also affects the soil freeze/thaw processes through soil water phase change and changing physical properties such as soil thermal and hydraulic conductivity (Scherler et al., 2010). Higher soil moisture content is generally associated with a longer zero-curtain period, and thus delay soil freeze/thaw onsets (Luo et al., 2014; Jiang et al., 2018). Tibetan Plateau soils are usually unsaturated and soil moisture shows a strong heterogeneity both vertically and spatially (Yang et al., 2013a), and how it affects the Tibetan Plateau soil freeze/thaw dynamics and permafrost changes remains under investigated (Yang et al., 2010). Moreover, although soil organic content in the Tibetan Plateau is relatively low compared with the northern high-latitude region, it can strongly influence soil thermal conditions due to its correlation with soil properties such as high soil porosity and high soil moisture content (Chen et al., 2012; Zhou et al., 2013).

In addition, surface conditions, such as vegetation cover and snow cover, act as important environmental controls on soil freeze/thaw dynamics and permafrost distribution. Vegetation cover affects the partition among the sensible, latent and soil heat fluxes, and therefore plays an important role in surface water and energy balances (Li et al., 2015a). Although most Tibetan Plateau permafrost region is dominated by alpine meadows or grasslands with sparse vegetation, Wang et al. (2012a) still found that decrease of alpine meadow and alpine swamps in the Tibetan Plateau were related to the increasing sensitivity of soil to climate changes and the greater shifts in soil temperature and water dynamics. Furthermore, different types of vegetation cover may exert different impacts on soil thawing (Wang et al., 2012b). Winter snow cover also has an important effect on soil freeze/thaw dynamics and permafrost temperature (Zhang, 2005; Yi et al., 2015). Snow cover plays an important role in determining how soil responds to surface warming due to its strong insulation effects and impact on surface energy balance associated with changes in surface albedo and snow water phase change (Zhang, 2005). Different from the overall thicker snow cover in the northern high latitude region, snow in the Tibetan Plateau often melts quickly due to strong solar radiation, and snow cover is generally shallow and ephemeral, with overall low albedo of fresh snow and limited insulation effects (Wang et al., 2020; Zheng et al., 2020). Therefore, snow cover in the Tibetan Plateau may have a cooling effect on underlying soil temperature due to the dissipated latent heat resulted from frequent snow melting or sublimation (Zhu et al., 2017). Moreover, snow meltwater that infiltrates into the soil could result in additional soil temperature fluctuations due to soil heat transport through convection and soil water phase change (Scherler et al., 2010; Luo et al., 2014).

# REGIONAL MONITORING APPROACHES AND ASSOCIATED CHALLENGES

## Remote Sensing of Tibetan Plateau Permafrost

### Current Progress

The sparse distribution of *in-situ* observation sites over the Tibetan Plateau (**Figure 1**) highlights the potential of satellite remote sensing to significantly improve regional permafrost monitoring across Tibetan Plateau. Remote sensing technology, including optical, near- and thermal-infrared, passive and active microwave remote sensing, has been used to directly or indirectly monitor the near-surface soil freeze/thaw and permafrost state in the Tibetan Plateau. The wavelength ranges from 0.4–0.7, 0.7–3.0, and 3.0–100 μm for optical, near- and thermal-infrared remote sensing, respectively; microwave remote sensing covers the spectrum from 1 mm to ~1 m in wavelength and has a much deeper penetration depth (Ulaby et al., 1982). Optical and near-infrared remote sensing are often used to detect the vegetation canopy and land surface properties, while microwave sensors can provide information on land surface moisture and temperature variations due to strong sensitivity to changes in land surface dielectric properties and emissivity. The applications of remote sensing in permafrost can be largely grouped into two categories: 1) identifying and mapping surface features and objects typical for permafrost areas; and 2) retrieving physical variables directly or indirectly relevant to subsurface thermal conditions (Tedesco, 2014). The first category was dominated by the application of high spatial-resolution optical and near-infrared images, while the second category covers a wider range of remote sensing systems from optical to microwave sensors as discussed below.

### Permafrost Monitoring Using Optical and Infrared Remote Sensing

Optical and near-infrared remote sensing with high spatial resolutions (<100 m) has been widely used to identify geological structures and landscapes associated with permafrost, e.g., hummock, thermokarst lakes, freeze/thaw boils, and surface classification, which can be used to infer the presence of underlying permafrost (Panda et al., 2010; Wang et al., 2014; Niu et al., 2018; Ran et al., 2018; Huang et al., 2020). Data from some high-resolution satellites such as Landsat-8 and GaoFen-1, 2, can be used to extract the landscape features and structures (Niu et al., 2018). This is especially useful for permafrost research in mountain regions characterized by heterogeneous surface condition like Tibetan Plateau. On the other hand, optical and near-infrared remote sensing can also provide information on land surface variables that can be used as auxiliary data to empirical or process-based models to infer the permafrost thermal state (Wang et al., 2014; Dai et al., 2018; Ran et al., 2018). For example, regional snow cover extent, surface albedo and vegetation cover products, which are available from optical sensors such as MODIS (250-m resolution), Landsat (30-m resolution), and Sentinel-2 (20-m resolution), have been used as model ancillary inputs to simulate the permafrost thermal state due to significant influences of vegetation and snow cover on

surface energy and water balance (Niu et al., 2018; Zheng et al., 2019b). In addition, many thermal infrared satellite systems (e.g., Terra, Aqua, and geostationary platforms like GOES and METEOSAT) could monitor the land surface temperature at spatial resolutions of 1–50 km, which is more directly linked to the subsurface ground thermal state (Holmes et al., 2009). Optical and thermal infrared remote sensing can provide information at high spatial resolution; however, it should be noted that factors such as frequent clouds and mixing pixels will introduce large uncertainties to these land surface products, and affect their application in permafrost studies (Kou et al., 2017).

Optical and thermal infrared imaging methods provide valuable regional datasets; however, permafrost is essentially a subsurface phenomenon and these methods are limited to imaging the land surface. Permafrost monitoring requires knowledge of soil temperature and heat transfer at deep layers; therefore, statistical or empirical models have been developed to utilize surface parameters derived from optical and infrared remote sensing to map permafrost extent and distribution (Zou et al., 2017; Aalto et al., 2018; Obu et al., 2019). Statistical models, e.g., decision tree or logistic regression models, have been applied to Tibetan Plateau permafrost mapping through building relationship between permafrost indices and multiple environmental factors including satellite-based land surface temperature and snow cover extent products. More recent studies are also developed using deep learning methods to create Tibetan Plateau permafrost maps (Wang et al., 2019a; Huang et al., 2020). Empirical models such as the TTOP (temperature at the top of permafrost) model and Kudryavtsev model that are derived from simplified heat transfer equations and require fewer inputs have been also widely used in Tibetan Plateau permafrost mapping (Zhao et al., 2017a; Zou et al., 2017).

### Permafrost Monitoring Using Microwave Remote Sensing

Microwave remote sensing shows strong sensitivity to soil dielectric changes induced by landscape and particularly soil freeze/thaw state, and can operate under all-weather conditions (Ulaby et al., 2014); therefore, it has been widely used to map surface soil freeze/thaw status and permafrost changes in both high latitude and high elevation regions (e.g., Li et al., 2012a; Li et al., 2013; Park et al., 2016).

Brightness temperature (Tb) measured by passive microwave remote sensing is associated with changes in surface emissivity and temperature conditions, both of which are closely associated with soil freeze/thaw status. Depending on the frequency and its penetration ability, relatively higher frequency (e.g., Ka-band, ~27–40 GHz) is commonly used to detect the freeze/thaw state of landscape surface elements, while lower frequencies such as L-band (~1–2 GHz) and P-band (~250–500 MHz) provide enhanced sensitivity to soil surface and profile freeze/thaw conditions (Du et al., 2015; Naderpour and Schwank, 2018). The Tb at Ka-band shows less sensitivity to freeze/thaw induced changes in surface emissivity, and is more correlated with land surface temperature especially for the vertical polarization (Holmes et al., 2009). A negative spectral gradient between 18 and 37 GHz was also found for the frozen soils due to volume

scatter darkening within the frozen soil (Zuerndorfer and England, 1992). Therefore, a combination of low Tb37V (37 GHz Tb at vertical polarization) and negative 18–37 GHz spectral gradient values has been widely used in frozen soil classification (Zhao et al., 2011; Han et al., 2015). Surface conditions such as dry snow may confound the soil freeze/thaw classification, and a number of groups have explored combining different indices to identify different surface conditions. For example, Jin et al. (2009) developed a decision tree algorithm to classify surface soil freeze/thaw state, through incorporating Tb37V, polarization Tb difference at 19 GHz, and a scattering index to distinguish scattering and non-scattering surfaces. Zhao et al. (2011) developed a discriminant algorithm that employs the Tb37V and the quasi-emissivity of Tb18.7H based on model simulations and Fisher linear discrimination analysis of different surface ground conditions. More recent studies also explored the values of L-band Tb in soil freeze/thaw classifications due to its deeper penetration depth (~50 and ~5 cm for the frozen and thaw soils, respectively) (Rautiainen et al., 2016; Zheng et al., 2019a).

Despite with high revisit frequency (less than a few days), current passive microwave sensors have the spatial resolutions on the order of 10–50 km, which can add large uncertainties to freeze/thaw classifications in an area with high topographic relief like the Tibetan Plateau (Li et al., 2013). Alternatively, space-borne synthetic aperture radar (SAR) sensors provide measurements of radar backscatter at much finer scales (~10–100 m) but have a much longer temporal revisit (>10 days). SAR signals share similar frequency-dependent responses to vegetation canopy and surface soil dielectric changes as microwave emission techniques, and radar backscatter at different frequencies (eg C-band, ~4–8 GHz; Ku-band, ~12–18 GHz) can be potentially used to characterize surface freeze/thaw and soil moisture status in the Tibetan Plateau (Van der Velde and Su, 2009; Han et al., 2011). The integration of active and passive microwave remote sensing provides a promising way to monitor surface and soil freeze/thaw and soil moisture states of Tibetan Plateau permafrost, leveraging the strengths of each method (Dente et al., 2014). A few studies also explored the value of combining passive microwave remote sensing and MODIS land surface temperature for high-resolution freeze/thaw mapping in the Tibetan Plateau (Zhao et al., 2017b; Kou et al., 2017).

More recently, interferometric synthetic aperture radar (InSAR) has shown great potential for regional mapping of active layer thickness. InSAR works by detecting surface deformation resulting from soil freezing induced uplift and thawing induced subsidence through measuring the phase shifts between repeat pass SAR images acquired at different times (Liu et al., 2012; Li et al., 2015b; Daout et al., 2017; Jia et al., 2017; Wang et al., 2018). It should be noted that this technique requires repeat passes to be obtained with less than 5 m deviation to enable accurate interferograms and phase shifts to be produced. Different techniques have been developed to generate interferograms and reconstruct the long-term series and seasonal trends in the surface deformation, which are linked with the long-term permafrost thaw and seasonal active layer thawing rate,

respectively. Empirical approaches have been used to convert the surface deformation to active layer thickness assuming a uniform soil saturation profile (e.g., Liu et al., 2012; Jia et al., 2017). A more recent study accounts for *the soil saturation differences* among different land cover types in the Tibetan Plateau (Wang et al., 2018), which results in different response curves of surface deformation to thaw depth. Li et al. (2015b) developed a new approach that uses the time lag between the periodic features of InSAR-observed surface deformation and land surface temperature to estimate the time interval between maximum surface air temperature and maximum seasonal thaw depth.

## Challenges

Currently, there are no direct remote sensing methods to detect deeper soil freeze/thaw and thermal conditions. Most satellite detection of soil freeze/thaw is generally limited to upper soil layer within a few centimeters of the surface. A potential approach to overcome this limitation is to introduce lower frequency sensors such as P-band SAR for soil profile characterization (Chen et al., 2019) and incorporate multi-frequency microwave observations such as joint L- and P-band SAR for enhanced delineations of soil profile freeze/thaw characteristics (Du et al., 2015). On the other hand, algorithms that can link surface properties and soil freeze/thaw indices to permafrost properties still need improvements. For example, most methods using InSAR derived surface deformation to estimate active layer thickness either ignore the effects of vertical variability of soil water content and soil properties (Liu et al., 2012; Li et al., 2015b; Jia et al., 2017), or use site-specific soil moisture profiles (Wang et al., 2018). This can introduce non-negligible errors when upscaled to the broader Tibetan Plateau, which is characterized by strong heterogeneous soil conditions, deep active layer and more variable soil moisture profiles. A drier surface layer can result in a delayed thawing subsidence period, comparing with the Arctic permafrost region (Daout et al., 2017). In addition, prior knowledge of ground ice content is important to interpret the long-term trend of surface deformation, but such information is still lacking at regional scale in the Tibetan Plateau.

Current satellite sensors still cannot provide measurements with sufficient spatial and temporal resolution to meet requirements for regional soil freeze/thaw and permafrost monitoring in the Tibetan Plateau. Satellite passive microwave remote sensing measurements are available at 10–50 km resolutions, which may not accurately represent the surface and subsurface conditions for each resolution element, especially in the heterogeneous mountain regions (Li et al., 2014). In addition, ambiguity often exists in the remote sensing retrievals using a single frequency due to its sensitivity to multiple land surface properties. More comprehensive evaluations on the accuracy of current satellite measurements or retrievals should be conducted through integrating point-scale in-situ measurements, multi-resolution satellite observations and forward radiative transfer model simulations (Dai et al., 2017). Moreover, it is highly desirable to understand the scaling effects of freeze/thaw state and bridge the multi-sensor retrievals especially for landscape freeze/thaw monitoring over complex terrain and diverse land cover types (Li et al., 2014; Du et al.,

2015). On the other hand, the Tibetan Plateau is characterized by large diurnal temperature range and rapid freeze/thaw changes, with long freeze/thaw transition periods (up to a few months) (Jin and Li, 2009). Therefore, remote sensing data with finer temporal resolution are needed for better monitoring the diurnal freeze/thaw cycles in the Tibetan Plateau permafrost area.

## Process-Based Modeling of Tibetan Plateau Permafrost

As mentioned above, current satellite remote sensing is largely restricted to the measurements of near-surface soils and their properties, while *subsurface* properties are more relevant to permafrost conditions. Many studies have combined satellite remote sensing data with empirical or statistical models to estimate the presence of permafrost as discussed above. However, these models usually oversimplify or overlook key processes controlling soil freeze/thaw and permafrost dynamics (Zheng et al., 2019b). Additionally, simple models also generally assume that the frozen subsurface is in equilibrium with the current climate, which may not capture the transient changes in frozen ground (Zhao et al., 2017a). Process-based models can better represent the underlying processes with the potential to provide more reliable estimates of regional permafrost distribution and changes.

### Current Progress

Frozen soil parameterizations in early process models was implemented using analytic or approximate solution of Stefan problem due to computational limitations (Li and Koike, 2003). With increased computational power, numerical models with high precision have been widely used in Tibetan Plateau. Most numerical models simulate the soil temperature in one dimension by employing a finite-difference or finite-element form of heat transfer equation, while many of them also consider other processes such as soil water migration, and link soil freeze/thaw process with hydrological process (Riseborough et al., 2008). A range of models have been used to model Tibetan Plateau permafrost distribution and changes, including soil process model GIPL2.0, land surface model CoupModel, CLM, and some hydrological models incorporating soil freeze/thaw scheme into water transfer process like VIC and GBEHM (Geomorphology-Based Eco-Hydrological Model) (Guo and Wang, 2013; Lan et al., 2015; Qin et al., 2017; Zheng et al., 2019b).

Earlier permafrost models like GIPL 2.0 (Qin et al., 2017) do not simulate surface energy balance, and usually directly set land/ground surface temperature as the upper boundary condition for soil heat transfer. These models are able to simulate soil temperature for deep layers which could be used to identify the presence of permafrost, while other processes like surface energy balance, snow melting are generally not included (Qin et al., 2017; Sun et al., 2019). These models have relatively lower requirements on climatic forcing data and usually use land/ground surface temperature and external soil moisture data as inputs. Despite the simplified heat-water transfer processes, it can reduce the uncertainties that may be introduced by external inputs such as highly uncertain precipitation data in the Tibetan Plateau. Nevertheless, current soil moisture products available from global satellite remote sensing and land model data assimilation system also show large uncertainties in the Tibetan Plateau region (Yang et al., 2013a; Zhao et al., 2014; Chen et al., 2017). In addition, although using ground surface temperature as upper boundary conditions can reduce the need of calculating surface energy balance budget, those data may not be widely available at the regional scale. The remotely sensed land surface temperature can be used as a substitute, but the difference between ground surface temperature and land surface temperature can be large due to the buffering effects of surface vegetation or snow cover (Luo et al., 2018; Luo et al, 2020).

A number of regional and global land hydrological models are also adapted for permafrost simulation in the Tibetan Plateau region (**Table 1**). Some hydrological models link the soil freeze/thaw scheme with hydrological-related process. For example, GBEHM model is developed from a hillslope-based hydrology model (GBHM) (Yang et al., 2015; Zheng et al., 2019b). Land models describe the complex land system, and therefore often include many processes related to soil freeze/thaw, such as surface energy balance processes, snow melting and infiltration process, soil water migration, and variability in soil thermal properties due to soil organic content changes etc. In addition to traditional numerical solution used in most models, there are also some variations in the model concepts and solution in recent models. For example, there is a new solution of 1-D heat transfer based on enthalpy in a land surface model HydroSiB2, showing good performance in soil freeze/thaw modeling in the Tibetan Plateau (Bao et al., 2016; Wang et al., 2017). These models have been applied to either site scale or regional scale in the Tibetan Plateau, with differences in the forcing data and representations of essential physical processes.

The parametrizations or representations of hydrological and thermal processes are different among different land hydrological models, such as the soil column depth and lower boundary conditions (**Table 1**), resulting in varying model performance. For example, SHAW model assumes that the soil thermal conductivity is a weighting average of various components in the soil, while CoupModel calculate the soil thermal conductivity based on three soil freeze/thaw state (i.e., unfrozen, frozen and partially frozen). Yang et al. (2013b) compared the simulation results from CoupModel and SHAW model at northern Tibetan Plateau sites, and found that soil heat transfer scheme used in CoupModel showed a better performance than SHAW model. Usually, these models require meteorological forcing including air temperature, wind speed, precipitation and radiation to solve the surface energy and water balance. It is generally difficult to directly use satellite data (such as land surface temperature) to drive these land models, which imposes additional difficulties for high-resolution (∼≤1 km) simulations as high-resolution surface meteorology datasets are not readily available in the Tibetan Plateau. Moreover, most land surface models are originally developed for surficial soil layers with a focus on the energy and mass exchange between the surface and the atmosphere, and therefore generally have simplified representation of the soil properties and thermal processes in deep soil layers (Sun et al., 2019).

**TABLE 1** | Comparisons of models used for Tibetan Plateau permafrost simulation. All models include soil heat transfer process, which is not included here.

| | Time step | Forcing data | Soil water transfer | Surface energy balance | Snow | Soil organic | Soil column depth | Lower boundary condition | Reference |
|---|---|---|---|---|---|---|---|---|---|
| SHAW | 1 h/daily | Tair, prec, W, SW, Q | ✓ | ✓ | ✓ | — | User defined | User defined model-estimated Tg | Liu et al. (2013) |
| CoupModel | 10 min/1 h/daily | Tair, prec, W, SW, Q… | ✓ | ✓ | ✓ | ✓ | User defined | User defined model-estimated Tg | Zhou et al. (2013) |
| GBEHM | Daily | Tair, prec, CF, Q, pres, land surface temperature | ✓ | ✓ | ✓ | — | User defined | Assigned geothermal flux | Yang et al. (2015) |
| GIPL2.0 | Daily | Tg0[a] | No | No | No | No | User defined | Assigned geothermal flux | Qin et al. (2017) |
| CLM | 3 h/daily | Tair, prec, W, SW, LW, Q, pres | ✓ | ✓ | ✓ | ✓ | 45.1 m | $g = 0$ | Guo and Wang (2013) |
| Noah | 30 min/3 h | Tair, prec, W, SW, LW, Q, pres | ✓ | ✓ | ✓ | ✓ | 40 m | Estimated Tg at 40 m | Wu et al. (2018) |
| VIC | 1 h/3 h/daily | Tair, prec, W, SW, LW, Q, pres | ✓ | ✓ | ✓ | ✓ | 50 m | $g = 0$ | Lan et al. (2015) |

Note: Tair, air temperature; Prec, precipitation; W, near surface wind speed; SW, downward shortwave radiation; LW, downward longwave radiation; Q, specific humidity; Pres, air pressure; CF, cloud fraction; Tg, soil temperature; g, soil thermal gradient.
[a]The required parameter is not listed in the table.

## Challenges

Large uncertainties exist in the reanalysis data, surface meteorology, surface and soil datasets in the Tibetan Plateau region, which are required for model inputs and parameterization, limiting a comprehensive evaluation of model processes and structure across the region (Dai et al., 2019). Ground-based meteorological data are particularly sparse in the Tibetan Plateau, with current stations mainly located in the central plateau and along the Qinghai-Tibet Railway/Highways, and complex topography adds additional challenges to upscaling local meteorological data to regional scale. For example, Zheng et al. (2019b) showed that the uncertainties associated with the extrapolation or interpolation of meteorological data were comparable to the uncertainties of model parameterizations. Previous studies also found that similar uncertainties were associated with model simulated frozen ground using different atmospheric forcing data comparing with model simulations using different parameterizations (Wang et al., 2016a; Guo et al., 2017). On the other hand, meteorological forcing data generated from global climate models has a coarse spatial resolution and cannot represent the local or small-scale climate variability (Su et al., 2013; Westermann et al., 2015). The unique topography and strong heterogeneous surface conditions in the Tibetan Plateau make it particular challenging to downscale coarse-resolution meteorology datasets (Yue et al., 2016). A recently released China meteorological forcing data incorporating meteorological stations, satellite data and re-analysis data has somewhat improved quality in the Tibetan Plateau and has been widely used; however, its uncertainty remains higher in the Tibetan Plateau than other regions of China (He et al., 2020). In addition, regional-scale soil datasets in the Tibetan Plateau, including soil properties (such as soil texture and soil organic carbon content), soil depth and ground ice content are extremely limited, which are important for model parameterization due to their significant impacts on soil heat and water transfer (Chen et al., 2015b; Cao et al., 2019).

Process representation in current models also needs improvement. A large gradient can exist in the surface air-ground temperature in the Tibetan Plateau region due to arid climate and high solar radiation (Wang and French, 1995). Without accounting for this temperature gradient, large biases can exist in the model simulated soil temperatures. Soil properties in global land models are generally derived from agriculture soil samples, while the physical properties of gravel soils in Tibetan Plateau are less considered (Yi et al., 2018a). Although most models have coupled soil heat transfer with soil water movement, the soil moisture profile is not generally well represented, partly due the complex interactions between topography, soil organic carbon content, vegetation distribution and their coupled effects on the dynamics of soil moisture (Wang et al., 2012a). Some key factors affecting the soil heat transfer unique to the mountain areas are also not adequately represented in current models (Zhou et al., 2013). For example, lateral water flow is generally ignored in most models, which may be of particular importance in the mountain areas (Zheng et al., 2019b). Simulating ground ice content in the

Tibetan Plateau permafrost is also a challenge. Accurate representation of ground ice content especially near the permafrost table will have a large impact on projecting future permafrost dynamics due to potentially large latent heat release and thermokarst activity as a result of thawing ground ice (Chen et al., 2015b; Liljedahl et al., 2016). On the other hand, model performance is highly affected by boundary and initial conditions, which vary greatly among models. Zero heat flux at lower boundary is widely adopted in most land models, while the geothermal gradient in the Tibetan Plateau show high spatial variability (Wu et al., 2010). Assigning a zero or constant geothermal flux might lead to large biases in model simulated deep soil temperature and permafrost depth especially at longer time scale (Xiao et al., 2013). More data on deep-soil layer like borehole observations are needed to improve deep soil parameterization and representation of lower boundary conditions in the permafrost models.

## Integrate Remote Sensing Data With Process-Based Models to Improve Tibetan Plateau Permafrost Monitoring

Remote sensing can provide spatially continuous landscape and climatic forcing data across large scale, which is especially useful for regional modeling in a heterogeneous terrain like the Tibetan Plateau. Here we summarize recent efforts that use multi-source remote sensing datasets to improve regional modeling of Tibetan Plateau permafrost or closely related environmental parameters, through model initialization, parameterization and data assimilation.

Climatic factors (such as air temperature and precipitation) in the Tibetan Plateau area show *evident elevation dependence.* In many process-based simulations, the SRTM (Shuttle Radar Topographic Mission) DEM (Digital Elevation Model) is used as a basis to extrapolate the *in-situ* meteorology observations to regional scale and generate model forcing data (e.g., Guo and Wang, 2013; Gao et al., 2018). However, in addition to elevation, other factors such as vegetation, soil wetness, slope, and aspect, also play *important roles* on the regional climate variability, and large uncertainties may exist in the spatial extrapolation using sparse ground observations (Wang et al., 2019b; Zheng et al., 2019b). Previous studies found that MODIS land surface temperature is able to capture the spatial pattern of near-surface air temperature and is especially useful in reducing the spatial interpolation errors in data-scarce regions (Zhu et al., 2013; Shamir and Georgakakos, 2014). In the northeast Tibetan Plateau, Wang et al. (2016b) used the lapse rate derived from MODIS land surface temperature product during the spatial interpolation of air temperature, and found the model simulated snow processes was improved comparing with simulations using the interpolated air temperature data. Regarding precipitation, previous studies found that the precipitation-elevation relationship contrasts between the northern and southern Tibetan Plateau, and the satellite-based precipitation data can approximately capture such patterns (Tang et al., 2018; Wang et al., 2019b). Nevertheless, very few studies have investigated the impacts of such satellite-based improvements in spatial extrapolation of climatic forcing on frozen soil simulations.

In addition to producing regional climatic forcing data, satellite remote sensing data has been also directly used as model parameters, such as vegetation coverage, slope and aspect, to improve regional simulations of Tibetan Plateau frozen ground. For example, based on the SRTM DEM, Zhang et al. (2018) quantified the topographic effects of solar radiation on permafrost distribution in the northeast Tibetan Plateau and the simulated permafrost coverage increased by 8% when accounting for the impact of topographic shadows on surface energy budget. Li et al. (2019) found that introducing MODIS-based vegetation coverage data into the CoLM can reduce the warming biases in land surface temperature and surface soil temperature by ~10°C in sparse vegetated areas in the Tibetan Plateau. Jin and Li (2009) assimilated the satellite microwave-based brightness temperature into SHAW model at the Amdo station in the central Tibetan Plateau, and found that the errors of simulated upper (0–2.58 m) soil temperature during wintertime reduced by 0.76°C. Through assimilating *in-situ* soil moisture data, Zhou et al. (2008) found the accuracy of frozen depth simulation has improved.

A process-based model fully driven by satellite observations would bridge the data gap in data-scarce region such as the Tibetan Plateau with the potential to improve regional permafrost simulation. As discussed above, most process-based models heavily rely on surface meteorological forcing data (Zheng et al., 2019b; Guo et al., 2017), while satellite observations are not fully consistent with the requirements of these models. For example, satellite remote sensing is not able to observe the near-surface wind speed, which, however, is an essential factor in solving the surface energy balance. In a recent study, Zheng et al. (2019b) used a maximum entropy production-based parameterization of surface energy balance to replace the originally turbulent theory-based scheme in GBEHM to make it fully driven by satellite data and capable of capturing the water-heat coupled processes within soil layers. The model was applied to simulate the frozen soil distribution and recent changes across the entire Tibetan Plateau (Zheng et al., 2020). The satellite-based model simulations showed overall higher accuracy, comparing with previous Tibetan Plateau permafrost maps generated using ground-based measurements (**Figure 3**, adapted from Zheng et al., 2020). In addition to the physics-based scheme, machine learning and artificial intelligence have also obtained reliable performance in solving the surface energy budget (Adnan et al., 2017; Zhao et al., 2019) as well as in regional permafrost mapping (Pastick et al., 2015; Aalto et al., 2018). A hybrid approach that combines machine learning-based surface energy balance and process-based heat-water coupled processes seems to be a potentially useful tool for regional mapping of Tibetan Plateau permafrost, while such studies are still lacking.

Although currently there are very limited studies using satellite data to directly improve model performance in simulating Tibetan Plateau permafrost through data assimilation, many efforts have been devoted to improving the simulation of variables closely related to the permafrost thermal state, such

**FIGURE 3 |** Mean spatial patterns of permafrost distribution **(A)** and active layer thickness **(B)** over the Tibetan Plateau during the period of 2002–2016, simulated using a remote sensing driven hydrology model (Zheng et al., 2019b; Zheng et al., 2020). The satellite-based permafrost map indicates that permafrost and seasonally frozen ground account for ~37% and ~56% of the Tibetan Plateau respectively, with an overall accuracy of 79.3–90.7% in identifying permafrost boreholes and 76.5–86.4% in identifying seasonally frozen ground boreholes. The accuracy is generally higher than permafrost maps generated using ground-stations, which demonstrates the advantage of satellite remote sensing-based methods in simulating frozen soils in data-scarce regions.

as soil moisture (Zhao et al., 2014; Yang et al., 2020), snow cover and snow depth (Zhang et al., 2014; Wang et al., 2020), and other key environmental variables including air temperature and net radiation (Li et al., 2012b; Lin et al., 2016). Through assimilating the satellite-based microwave brightness temperature at 6.9 and 18.7 GHz, Yang et al. (2007a) found the accuracy of simulated surface energy budget was improved. Lin et al. (2016) found that assimilating MODIS snow cover would be especially important in reducing uncertainties in air temperature predictions in the Tibetan Plateau. Those results could potentially improve the model simulated soil thermal regime and thus permafrost distribution. Despite its potential advantages in improving frozen soil simulation, the application of data assimilation is greatly limited due to large uncertainties in current satellite products and retrieval algorithms in the Tibetan Plateau (Chen et al., 2017). In addition, satellite-based soil moisture and snow cover retrievals from passive microwave remote sensing data have generally coarse spatial resolution, and appropriate downscaling scheme is needed to characterize the spatial heterogeneities within the coarse-grid in the mountain areas (Zhao et al., 2014).

## DISCUSSION

## Unique Challenges in Tibetan Plateau Permafrost Monitoring

Unique environmental conditions in the Tibetan Plateau result in permafrost characteristics different from that in the northern high latitudes or other alpine environments as discussed above. The topography in the Tibetan Plateau is complex and characterized by strong heterogeneity at small spatial scales, exerting strong control on local permafrost distribution (Luo et al., 2012), while most satellite data or models have relatively coarse resolutions (>1 km) and cannot well represent such local-scale variability (Yang et al.,

2010). Moreover, the complex topography in the Tibetan Plateau can result in strong spatial heterogeneity in local-scale snow cover and land surface temperature conditions, which adds additional uncertainties to satellite-based freeze/thaw detection (Zhao et al., 2017b; Dai et al., 2018). For example, snow accumulated in shady areas can result in strong scattering, impacting the accuracy of coarse-resolution passive microwave remote sensing retrievals (Dai et al., 2017). Accurately accounting for the impact of topography on Tibetan Plateau soil freeze/thaw dynamics and permafrost distribution requires improved remote sensing algorithms and models.

Other surface or subsurface conditions affecting the Tibetan Plateau permafrost are also different from those in the high-latitude regions. The Arctic is mostly underlain by continuous permafrost (Brown et al., 1997), characterized by overall high soil carbon content, thicker snow cover and more saturated soil condition (Hinzman et al., 2013). Previous study showed the uncertainty in spatial and vertical soil organic distribution is the main factor affecting the model simulated active layer thickness in Alaska, followed by the impacts of soil moisture (Yi et al., 2018b). The timing and amount of snow cover also play an important role in affecting pan-Arctic soil temperatures, especially in deeper soils, due to its strong insulation effects (Yi et al., 2015; Jones et al., 2016). However, the frozen ground in the Tibetan Plateau is generally characterized by unsaturated soils, low organic carbon content, shallow snow cover, and shorter snow duration (Li et al., 2008; Kang et al., 2010). Large uncertainties exist in Tibetan Plateau remote sensing and model soil moisture products due to strong spatial and vertical variability in soil moisture. The uncertainties limit their usefulness in regional permafrost monitoring (Han et al., 2015; Bi et al., 2016). For example, most InSAR-based active layer retrieval algorithms assume a saturated soil profile within the active layer, while Tibetan Plateau permafrost generally shows a much deeper and drier active layer compared with that in the

Arctic region (Jia et al., 2017). Other Tibetan Plateau environmental factors also need to be carefully considered in model parameterization. For example, the insulation effects of soil organic carbon in the Tibetan Plateau is likely limited due to its lower content; however, soil carbon content can significantly affect Tibetan Plateau soil freeze/thaw dynamics through altering the soil hydraulic properties and soil moisture distribution (Zhou et al., 2013; Jiang et al., 2020). Shallow snow cover may have a cooling effect on subsurface soil temperature through reducing the absorption of solar radiation (Wang et al., 2020). In addition, the coarse-fragment soil with a larger thermal conductivity is widespread in the Tibetan Plateau, unlike the prevailing peat soils in the Arctic. This should be considered in the model parameterization when simulating the Tibetan Plateau permafrost (Arocena et al., 2012; Pan et al., 2017; Yi et al., 2018a).

## Potential of Geophysical Measurements in Regional Permafrost Studies

Current satellite remote sensing cannot directly detect deep soils and the permafrost, while geophysical techniques have been proven to be useful for subsurface soil characterization and permafrost detection in a minimally invasive manner. Examples of geophysical approaches include thermistors and dielectric sensors, ground penetrating radar, and electromagnetic methods (Dafflon et al., 2016). Among these techniques, electromagnetic methods are becoming increasingly popular, which calculates the ground conductivity or resistivity through measuring the changes in the eddy currents and induced magnetic fields in the subsurface (Hauck et al., 2001). Based on the distinct difference of resistivity between frozen and unfrozen materials, the electromagnetic method can detect permafrost existence with a relatively high spatial resolution. It has the advantage of being sensitive to the liquid soil water content, and providing information on the structure and content of the deep soil layer, which is lacking but usually required by models (Minsley et al., 2012; Mikucki et al., 2015). In addition to the surface geophysical measurements, airborne electromagnetic methods have been widely used in the polar regions to detect the permafrost over diverse landscapes at the regional scale (Minsley et al., 2012; Rey et al., 2019). Airborne electromagnetic methods have less terrain-induced noise than ground measurements, and may be particular useful for permafrost mapping in mountain regions (Hauck et al., 2001; Su et al., 2020), while such applications are still lacking in the Tibetan region.

The geophysical measurements in combination with other datasets have shown great potential to improve model representation of subsurface properties in permafrost region. For example, Dafflon et al. (2016) combined electromagnetic method and other types of observations, and successfully mapped subsurface variability in polygon shaped Arctic tundra area and document the key controls on the spatial distribution of soil properties. Léger et al. (2019) used the soil temperature data from a spatially distributed temperature profiling system and electrical resistivity data to identify correspondences between surface and subsurface property distribution in discontinuous permafrost regions. The results from these studies provide the basis for model parameterization and initialization, while other studies have directly used such observations to improve process representation in the permafrost models (Tran et al., 2017, Tran et al., 2018). Due to strong influences of organic carbon content on soil hydrological-thermal parameters, Tran et al. (2017) performed joint inversion of multiple datasets including soil temperature, moisture and electrical resistivity data to estimate the soil organic carbon profile along a transect in Barrow, Alaska, through linking the petrophysical and geophysical models with the CLM model. Combining the CLM model and electrical resistivity data, a follow-on study further investigated the soil thaw depth and its controlling factor at a high spatiotemporal resolution over a long period (Tran et al., 2018). However, it should be noted that additional errors may be introduced into the model estimates due to uncertainties in electrical resistivity inversion method and retrievals.

## Improving Model Representation of Spatial Heterogeneity

An important feature of permafrost affected landscapes is the large spatial heterogeneity in soil active layer conditions, which are generally poorly represented in global land models (Muster et al., 2012; Mishra et al., 2017). Information on active layer soil conditions at landscape scales is needed to better represent the spatial heterogeneity and scaling functions in global models and reconcile coarser model simulations with more extreme local heterogeneity in active layer and permafrost conditions. Many studies have combined in-situ measurements, satellite remote sensing and models to address this problem. However, most studies focus on the high-latitude permafrost landscapes while Tibetan Plateau permafrost studies represent a relatively new research topic. Therefore, we summarize relevant studies in the high-latitudes, and hope to provide some insights for similar applications to the Tibetan Plateau region.

Local to landscape scale variations in active layer conditions can be effectively monitored using in-situ ground measurements (Brown et al., 2000; Romanovsky et al., 2010) or ground-based remote sensing including ground penetrating radar and electrical resistivity measurements (Hubbard et al., 2013; Schaefer et al., 2015). While these methods provide detailed assessments of active layer properties, they are generally applied over limited local areas ($<1 \, km^2$) and are unsuitable for mapping and monitoring over large regions. Regionally refined active layer products upscaled from carefully designed in-situ network measurements using remote sensing based geospatial data layers offer the potential to improve the representation of permafrost active layer properties in global land models. Earlier studies used empirical models driven by in-situ ground observations to map permafrost and active layer properties over larger areas (e.g., Anisimov et al., 2002; Panda et al., 2010). More recent studies used machine learning data-fusion approaches and remote sensing data, including optical-infrared and LIDAR data, to extend ground-based or airborne measurements to produce regional active layer and permafrost maps (Hubbard et al., 2013;

Pastick et al., 2015). Similar as active layer thickness, a variety of methods including geospatial analysis and machine-learning data-driven approaches have been applied to upscale *in-situ* soil organic carbon content and soil moisture measurements to provide grid-cell mean estimates at a large footprint for direct comparison with satellite or model-based products (e.g., Mishra and Riley, 2015; Clewley et al., 2017).

The above spatial analysis and datasets provide critically needed information on permafrost distribution for global model parameterization and validation (Mishra et al., 2017). Previous studies have demonstrated the importance of considering sub-grid scale variability in land cover and surface properties in large-scale global models to accurately simulate water, energy and carbon exchange in permafrost landscapes (Liston, 2004; Gouttevin et al., 2012). However, how to represent those local effects to facilitate upscaling of model simulated water, energy and carbon fluxes remains a challenge (Muster et al., 2012). Potential improvements may include statistical representation of spatial distribution and temporal changes in the surface variables related to permafrost properties. For example, Zhang et al. (2014) used statistical functions derived from field measurements to characterize the spatial variability of surface ground and soil conditions and incorporated this information into a process model to simulate the frequency of permafrost occurrence at very high spatial (<1 km) resolution. Much better accuracy in model simulated ground temperatures in Norway was achieved when using a gamma distribution to represent sub-grid variability in snow distribution than using grid-cell average snow depth (Gisnås et al., 2016). Yi et al. (2018b) also found the model better represented the statistical distribution of active layer thickness when using a logistic distribution consistent with the spatial distribution of surface wetness derived from the P-band radar data to represent sub-grid variability of organic layer thickness. In addition, the zonation approach can combine diverse datasets over different scales and identify the large-scale zones that have distinct properties, which can be used to characterize the spatial heterogeneity in complex permafrost environments. For example, Wainwright et al. (2015) employed a nested polygon geomorphic zonation approach to characterize the distributions of environmental properties in Arctic tundra and assess their impact on ecosystem carbon fluxes. The combination of zonation approach and emerging technologies such as machine learning approach can generate spatially-explicit datasets from a diverse range of observations supporting the model needs of parameterization and initialization, and may have great potential in permafrost research (Hubbard et al., 2018; Hubbard et al., 2020).

## RESEARCH PRIORITIES AND RECOMMENDATIONS

We have reviewed the state of knowledge for Tibetan Plateau permafrost, soil freeze/thaw state, and summarized recent progress in using satellite remote sensing data and models to monitor Tibetan Plateau permafrost. This exercise has revealed important gaps in capabilities for monitoring and modeling the current state of Tibetan Plateau permafrost as well as projecting its future trajectory. Here we recommend the following research priorities to address these gaps.

Satellite-based optical and infrared remote sensing provide high spatial resolution land surface conditions. These techniques have great potential for producing Tibetan Plateau classification maps and determining correlations between these classifications and permafrost distributions, especially in regional-scale applications. Particularly, high-resolution imagery (<10 m scale) can be used to capture the high degree of spatial heterogeneity in the Tibetan Plateau and further infer the related permafrost states, such as using high-resolution imaging of swamps, wetlands and small watersheds to monitor changes in the hydrologic state that may be coupled with local permafrost degradation.

Microwave remote sensing has shown great potential in surface freeze/thaw and permafrost monitoring due to its strong sensitivity to soil water content and phase changes, its ability to penetrate clouds, and providing all-weather monitoring of the land surface. However, current microwave remote sensing methods are limited to detections in the upper soil layer within a few centimeters of the surface. Deeper soil remote sensing requires lower frequency surveys (such as P-band SAR) and multi-frequency observations (such as joint L- and P-band SAR) to enable soil vertical profile retrievals. These sensors and corresponding algorithms should be developed. InSAR have been widely used to map regional subsidence and active layer thickness in the Tibetan Plateau, but more systematic subsidence mapping is still needed, with particular emphasis on the permafrost transition zone that is vulnerable to abrupt thaw and degradation. Improved approaches and regional data such as accurate DEM and soil moisture information are also needed to support InSAR active layer retrieval.

The apparent scarcity of local-scale observations greatly limits our process understanding in the Tibetan Plateau permafrost area. Therefore, we also call for the expansion of the *in-situ* sampling network, particularly in the western Tibetan Plateau, along the transition zones between discontinuous and sporadic permafrost zones, and along elevation gradients (**Figure 1**). Additional information on deep soil temperature, ground ice content, more consistent soil moisture and dielectric profiles, improved mapping of soil texture and soil organic content are required for improving remote sensing algorithms and regional models. Geophysical measurements especially airborne electromagnetic method can obtain information on deep ground structure and unfrozen water content, and provide more spatially extensive measurements than point-scale observations, and should be considered when expanding the local-scale observational network in the Tibetan Plateau.

Integrating local-scale observations, remote sensing data with process-based models will be an effective way to monitor regional permafrost and project its future state. However, a number of factors limit such applications in Tibetan Plateau permafrost research, including but not limiting to large uncertainties in current satellite products for the Tibetan Plateau area, mismatch between model input data needs and information provided by current satellite sensors, insufficient accounting for spatial heterogeneity impact on permafrost distribution.

Better approaches to combine diverse datasets at different spatial and temporal scales with models are needed to address the above challenges, and should be developed. In addition, current model scheme and parameterization also require improvements to better reproduce the unique soil freeze/thaw characteristics in the Tibetan Plateau region.

## AUTHOR CONTRIBUTIONS

YY initiated the study. HJ, GZ, and YY wrote the paper. Other co-authors contributed to the discussion and provided feedback.

## FUNDING

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